Causality in Travel Mode Choice Modeling: A Novel Methodology that Combines Causal Discovery and Structural Equation Modeling

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ABSTRACT
Causal discovery identifies causal relationships between variables in a dataset. This study investigates the potential of causal discovery in extracting causal connections from transportation behavioral data. To do so, four causal discovery algorithms are tested: Peter-Clark (PC), Fast Causal Inference (FCI), Fast Greedy Equivalence Search (FGES), and Linear Non-Gaussian Acyclic Models (LiNGAM). Their performances are compared to determine the most appropriate algorithm for travel choice modeling. Next, we propose a novel methodology to combine causal discovery with structural equation modeling (SEM) to model travel mode choice. This modeling approach can overcome some of the limitations of SEM, by combining both the strengths of causal discovery and SEM. The results show that LiNGAM best captures causality in transportation behavior modeling, among the four algorithms tested since the LiNGAM-based SEM achieved the lowest values of Chi-square, Root Mean Square Error of approximation (RMSEA), along with greater than 0.95 Comparative Fit Index (CFI), Goodness-of-Fit Index (GFI), and Adjusted Goodness-of-Fit index (AGFI), Normed Fit Index (NFI), and Tucker-Lewis Index (TLI). The modeling results provide insights in causal relations leading to choosing private vehicles, public transit, or walking as a travel mode. The analyses are conducted on data from the 2017 National Household Travel Survey in the New York Metropolitan area.

Keywords: Causal Discovery, Structural Equation Modeling, Travel mode choice modeling
INTRODUCTION

Understanding and modeling travel mode choice behavior is a classic problem in transportation (1). The long-established practice for conducting these studies is by utilizing statistical regression-based models, such as Linear Regression models, Multinomial Logit models, and Nested Logit models (2–5). These models make strong assumptions and require some underlying relationships between the variables that are often considered not realistic (3).

To overcome some of the limitations of traditional models, researchers have proposed a number of alternative methods for travel choice modeling, for example, Neural Networks, Extreme Gradient Boosting models, Random Forest, and Decision Trees to name a few (2,3,6–8). Another fairly popular alternative approach for modeling mode choice is a Structural Equation Model (SEM) (9). SEMs possess some distinct advantages over most of the other techniques. In particular, SEMs: (i) are capable of handling exogenous, endogenous, and latent variables; (ii) can account for indirect, multiple, and reverse relationships; (iii) accept non-normal data; and (iv) offer easier visualization of the modeled network (9).

Despite these advantages, SEMs have their limitations as well. A key limitation is an inherent property of these models. SEMs are confirmatory tools, not exploratory. Therefore, the modeler needs to provide a hypothesized structural graph to the SEM before running the model (10). As Bollen and Pearl (11) pointed out, “…the SEM represents and relies upon the causal assumptions of the researcher. These assumptions derive from the research design, prior studies, scientific knowledge, logical arguments, temporal priorities, and other evidence that the researcher can marshal in support of them. The credibility of the SEM depends on the credibility of the causal assumptions in each application.” Given the importance of these causal assumptions, constructing a reasonable, hypothesized causal graph can be challenging. This might be particularly true in case of large and complicated networks. Existing studies have usually had to rely only on domain knowledge and literature to build causal graphs. The lack of a dependable mechanism to generate a credible causal graph can create a substantial barrier in estimating a credible SEM. A common, yet flawed, process in SEM building has also been to alter a graph until the SEM achieves a reasonable accuracy. This process is deemed controversial and can lead to an overfitted, unstable, unreliable, and incorrect model (12–15).

To address this issue, we would like to turn the attention to Causal Structural Learning (CSL) techniques, also known as Causal Discovery. Causal Discovery represents techniques that can extract causal structures from observational data (16). These techniques are grounded in the complex concepts of causality, rooted in fields of statistics, economics, epidemiology, computer science, philosophy, and others (17). Causal Discovery can derive causal links between exogenous variables, endogenous variables, latent variables, and unobserved confounders. These causal connections offer insights into the complex causal relationships in a network which makes way for the study of the effect of hypothetical intercepts and counterfactuals directly from the observational data (18). Since Causal Discovery deals with causation, and not simply correlations, they are well suited to provide inputs for policy making.

We propose using Causal Discovery as a precursor to the SEM. The causal structure obtained from Causal Discovery would be fed as input to a SEM model. This union can be mutually beneficial. Causal Discovery, which is broadly non-parametric, gains parametric measures from the SEM, while the SEM benefits from the data-driven causal graphs extracted by the causal discovery algorithms to be used as its input. Since several causal discovery algorithms exist, differing in methodological approaches and assumptions (18), we selected four algorithms for this analysis. These algorithms are Peter-Clark (PC), Fast Causal Inference (FCI), Fast Greedy Equivalence Search (FGES), and Linear Non-Gaussian Acyclic Models (LiNGAM). To the best of our knowledge, these algorithms have never been used before in travel mode choice modeling.

The objective of this study is threefold. First, it is to apply causal discovery algorithms to estimate and study the causal relationships related to travel mode choice behavior. Second, it is to compare the performance of the four causal discovery algorithms to determine the most appropriate result for studying travel mode choice. Third, it is to introduce a novel methodology that combines Causal Discovery and SEM to model travel mode choice.
The next section reviews some of the relevant literature. It is followed by a methodology section that explains the theoretical concepts of Causal Discovery and SEM, and that discusses the proposed methodology and introduces the study dataset. Next, the result section presents the results from our analysis. Then, the discussion section examines the modeling results. Lastly, the conclusion section presents the conclusions, limitations, and the future work of this study.

LITERATURE REVIEW
Since ancient times, the idea of causality has attracted the attention of researchers, philosophers, and theorists (19–22). For more than a century, the scientific community has been aware that correlation is not causation (23). In spite of that, correlation was promoted as a scientific concept of universal significance (24), while causation subsided in the twentieth century scientific research (25). Nevertheless, statisticians still remained implicitly interested about causality when interpreting the results of their analysis (26).

The interest in causal methods reemerged in the sciences in the last decades of the twentieth century (25). During this time, causal reasoning began to be studied using Bayesian Networks (27), and the idea of extracting causal structures from raw data gained attention (28,29). In recent years, machine learning researchers in academia (30) as well as in industry (31) have gradually turned their eyes toward causality. Pearl and Mackenzie (32) have advocated the need to consider causality to build transparent, unbiased, and trustworthy Artificial Intelligence. Even with the increased interest in causality, it remains relatively new in scientific research and faces several challenges (32,33). The research on causality can be broadly divided in two categories: Causal Discovery and Causal Inference (17). While Causal Discovery is about learning causal structures from the data, Causal Inference involves estimating causal effects (17), assuming a pre-existing causal structure. In this study, we have limited our focus to Causal Discovery.

In recent years, the research on Causal Discovery has reached a broader scientific audience and to a wide variety of research fields like biology (34), economics (35), medicine (16), mental health (36), climatology (37), data science (30), and more. Despite its applications in diverse fields, only a limited number of studies have used Causal Discovery in Transportation, and particularly in mode choice modeling.

To the best of our knowledge, only three studies have applied Causal Discovery to model travel mode choice (4,5,38). Xie and Waller (4) applied a Bayesian Network and used both observational information along with cause-effect hypotheses to learn a causal graph for mode choice prediction. Similarly, Ma et al. (5) used Structure Learning and unsupervised Bayesian Networks with domain knowledge to infer a causal graph. They explored three different classes of learning algorithms: constrained-based algorithms, score-based algorithms, and model averaging, and they benchmarked their performance on a case study that investigates the mode choice of commuters traveling to Luxembourg. They found that the score-based algorithms perform the best. They also found that domain knowledge is useful to restrict the search space of possible causal graphs and that utilizing such common knowledge improves the predictive performance of the resulting graph. More recently, Monteiro (38) used a constrained-based causal discovery algorithm, Find One-Factor Cluster (FOFC), to estimate a causal graph for travel satisfaction as well as mode choice. The inferred graph was compared with a graph constructed based on domain knowledge. It was found that FOFC recovered many of the cause-effect relations but had an undesirable property of being dependent on the order of the inputs. They, however, saw some potential in FOFC to contribute to the hypothesis generation for SEM.

In contrast to Causal Discovery, SEMs are well-known in transportation. They have been widely used for travel mode choice modeling (9,39–41). Most of these studies, however, have been dependent on domain knowledge and literature to design the structure of SEM.

Our study seeks to fill the gap in the research in two important ways: (i) This study applies, analyzes, and compares some of the causal Discovery algorithms that have never been used before for mode choice modeling. These algorithms can not only confirm well established causal hypotheses, but they can also reveal new causal relationships in the data. Thus, this study contributes an important analysis of the usage of Casual Discovery in Transportation. (ii) Our proposed approach of combining
Causal Discovery and SEM can support modelers in making causal assumptions that are data driven, more substantiated, and more reliable than those usually made in past studies.

**METHODODOGY**

**Key concepts**

This subsection explains the main concepts relevant to this study.

**Structural causal model (SCM):** A structural causal model (42) is used to model the causal assumptions in a domain by representing the relevant features and their interactions. An SCM $M(V, U, f)$ models how nature assigns values to the variables of interest using a set of variables $U, V$, and a set of functions $f$ that assign values to each variable in $V$ using other variables. The variable set $U$ is termed as exogenous variables, which are external to the causal model and often considered errors or disturbances. The value of an endogenous variable $V_i \in V$ is explained by a function $f_i \in f$ of at least one exogenous variable $U_i \in U$ and optionally other endogenous variables i.e. $V_i = f_i(V_i, U_i)$, where $V_i \subset V \setminus V_i$ is a set of direct causes of $V_i$. Therefore, a variable is a function of its known direct causes and unknown disturbances.

**Causal graphical model:** The causal relationship among the variables in an SCM can be represented using a directed acyclic graph (DAG) $G(V, E)$ where $V$ and $E$ are a set of vertices and edges respectively. Each vertex (or node) has incoming edges from its direct causes. $V_i \rightarrow V_j$ denotes an edge from $V_i$ to $V_j$ where $V_i$ is the parent and $V_j$ the child. Two vertices are adjacent if there is an edge between them. A directed path is a sequence of nodes obtained following the direction of the edges. A graph is directed acyclic if there are no directed paths with repeated nodes. The nodes preceding the tail node of the directed path are the ancestors of the tail node. Similarly, the nodes following the head node of the directed path are descendants of the head node. Let the symbols $pa(V_i, G), anc(V_i, G)$, and $des(V_i, G)$ indicate the sets of parents, ancestors, and descendants of $V_i$ for graph $G$ respectively. The exogenous variables are assumed to be independent of each other and are not explicitly shown in the graph.

**Conditional independence relations:** The data generated by an SCM should adhere to the conditional independence relations that the causal graphical model entails. The joint probability distribution $P$ described by $G(V, E)$ factorizes to the product of the conditional probability of each random variable given its parents according to causal Markov assumption i.e.

$$P(V_i, V_2, \ldots, V_n) = \prod_{i=1}^{n} P(V_i | pa(V_i, G))$$  \hspace{1cm} (I)

The factorization in equation (I) follows from the chain rule of probability theory and conditional independence (CI) relations entailed from causal Markov assumption. With the causal Markov assumption, a random variable is independent of all other variables except its parents and its descendants conditioned on the parents, i.e., $V_i \perp V \setminus \{V_i \cup pa(V_i, G) \cup des(V_i, G)\} | pa(V_i, G)$. The Markov conditions are not all the conditional independence relationships captured by the causal model. The notion of $d$-separation (27) is used to read off all the conditional independencies that hold for any data distribution that is generated by the mechanism described by a graphical model. The rules of $d$-separation are formally defined with the help of three sub-graph structures: (1) chain, $V_i \rightarrow V_j \rightarrow V_k$, with unidirectional path, (2) fork, $V_i \leftarrow V_j \rightarrow V_k$, with a common cause, and (3) collider, $V_j \leftarrow V_i \rightarrow V_k$, with a common effect. An undirected path is said to be blocked by a node $V_j$ with a conditioning set $S$ of observed variables if one of two conditions hold: (i) $V_j \in S$ and $V_j$ is not a collider or (ii) $V_j$ is a collider and $V_j \in S \land \text{des}(V_j, G) \in S$. Two nodes are said to be $d$-separated by a conditioning set $S$ if all the paths between the nodes are blocked by $S$. The $d$-separated nodes are independent of one another conditioned on set $S$ (42).

**Causal structure learning:** Causal discovery is transformed to the problem of CSL (18) that concerns learning the adjacencies of nodes and the orientation of the edges in $G(V, E)$ using an observational distribution. The idea of CSL is to utilize conditional independence in the data distribution to infer the structure of the causal graphical model. However, the same conditional independence relation can be satisfied by multiple causal models belonging to a Markov equivalence class. For example, the conditional independence relation $V_i \perp V_k | V_j$ is satisfied by the fork sub-graph $V_i \leftarrow V_j \rightarrow V_k$ as well as
two chain sub-graphs $V_i \rightarrow V_j \rightarrow V_k$ and $V_i \leftarrow V_j \leftarrow V_l$. The causal structures entailing the same set of conditional independence relations belong to the Markov equivalence class. CSL generally concerns learning a Markov equivalence class of the underlying causal model. Additional parametric assumptions and background knowledge are needed to identify a causal model within the Markov equivalence class.

Assumptions: In general, CSL methods make assumptions about the underlying data generating mechanism to learn a causal structure from observational data. Two common assumptions are: (1) causal faithfulness that implies that all the conditional independencies observed from the data distribution are entailed by the $d$-separation conditions of an underlying causal graph, and (2) causal sufficiency that refers to the absence of any unmeasured common causes of variables in $V$. Additionally, most CSL algorithms make assumptions of no selection bias and infinite sample size. These common assumptions may be relaxed by some algorithms. The next subsection names the main assumptions behind the four causal discovery algorithms used in this study.

Causal Discovery algorithms

PC: PC (29,43) is a constraint-based algorithm that uses conditional independencies in the data as constraints to estimate an equivalence class of the underlying SCM. It makes assumptions about causal sufficiency and faithfulness for the correctness of edge adjacencies. Then, $\psi$-structure discovery followed by Meek rules (44) produces an equivalence class graph, also known as a completed partial directed acyclic graph (CPDAG). An undirected edge $V_i \xrightarrow{} V_j$ in a CPDAG suggests both orientations $V_i \leftarrow V_j$ and $V_i \rightarrow V_j$ are possible for given data, and additional knowledge is required for the orientation of the edge.

FCI: FCI (29) is another constraint-based algorithm that relaxes the causal sufficiency assumption of the PC algorithm. FCI outputs a partial ancestral graph (PAG) to incorporate the hidden confounders using a bidirectional arrow, i.e., $V_i \leftrightarrow V_j$. In a PAG, $V_i \rightarrow V_j$ is interpreted as $V_i$ being an ancestor of $V_j$ and $V_i$ not being an ancestor of $V_j$. Similarly, $V_i \leftarrow V_j$ indicates either $V_i$ is an ancestor of $V_j$ or there is a hidden confounder between $V_i$ and $V_j$.

FGES: FGES is an optimized and parallelized version of the Greedy Equivalence Search (GES) (45) algorithm. FGES is a score-based method that approaches CSL as the problem of fitting a causal graph that best describes the conditional independencies in the data using a relevant score function. GES starts with an empty graph and greedily keeps adding edges that increase the goodness-of-fit score. The algorithm then removes the edges until the score does not improve to return the equivalence class of DAGs with the maximum score. FGES makes the causal sufficiency assumption but allows some violation in the faithfulness assumption. FGES returns CPDAG as output similar to PC.

LiNGAM: LiNGAM (46) is a functional causal model-based (or equivalently structural equation model-based) CSL algorithm. The functional causal models (47) use SCM with additional assumptions on the distribution of $U$ and $V$ to distinguish between different DAGs in the same equivalence class. It assumes causal sufficiency, linear continuous data generating process, and exogeneous variables with non-Gaussian distributions of non-zero variance. The non-Gaussian nature of noise enables asymmetric cause-effect relationships that help in identification beyond the equivalence class.

This study uses BDeu test ID and BDeu score for PC, FCI, and FGES algorithms. More detail about the algorithms, their assumptions, statistical tests and scoring function can be found in these resources (18,48).

SEM

A SEM has two components – structural model and measurement model. The former is related to the hypothetical assumptions about the relations between the latent variables, while the latter deals with connecting latent variables to observed variables (49). Mathematically, the structural model can be represented as:

$$\eta_i = \alpha_n + B\eta_i + \Gamma\xi_i + \zeta_i$$  \hspace{1cm} (II)

where $\eta_i$ refers to vector of latent endogenous variable for unit $i$; $\alpha_n$ is vector of intercept terms for the equation; $B$ is matrix of coefficient giving expected effects of latent endogenous variables ($\eta$) on each...
other; \( \Gamma \) denotes coefficient matrix giving the expected effects of the latent exogenous variable (\( \xi \)) on latent endogenous variables (\( \eta \)); \( \zeta_i \) is vector of disturbances (49).

The measurement model can mathematically be represented by the following equations:

\[
\begin{align*}
y_i &= \alpha_y + \Lambda_y \eta_i + \varepsilon_i \\
x_i &= \alpha_x + \Lambda_x \xi_i + \delta_i
\end{align*}
\]

where \( y_i \) is the vector of observed indicator \( \eta_i \); \( x_i \) is the vector of observed indicator \( \xi_i \); \( \Lambda_y \) denotes matrix of factor loading or regression coefficients giving the impact of the latent variable \( \eta_i \) on \( y_i \); \( \Lambda_x \) denotes matrix of factor loading or regression coefficients giving the impact of the latent variable \( \xi_i \) on \( x_i \); \( \zeta_i \) is the unique factors of \( y_i \); \( \delta_i \) is the unique factors of \( x_i \) (49).

In this study, we estimated SEM using polychoric correlation based Unweighted Least Square (ULS) estimation method which is the recommend method for ordered categorical data (50). The reader is referred to resources (9,49–51) to know more about the estimation methods and goodness of fit measures.

**Data**

In this study, we used the 2017 National Household Travel Survey (NHTS) data (52). These are collected from a stratified random sample of U. S. households in all the 50 U.S. States and the District of Columbia. The data consists of information about each trip made by each household member on the household’s travel day. Table 1 shows the variables that were based on our domain knowledge and previous studies (4,5). These variables were discretized and converted to binary and ordinal variables to fit the requirements of the various causal discovery algorithms used.

To narrow the scope of this study, only the trips that were made using cars, public transport, or walking (as defined in Table 1) were studied. Additionally, any respondents of age less than 18 years were removed. Further, any trips with unknown values (for example, not ascertained, I don’t know, I prefer not to answer, appropriate skip) for trip purpose, trip length, household income, race, age, education, gender, or employment were removed from the dataset. Since the availability of transportation infrastructure varies substantially throughout the country and that could be affecting travel mode choices, we reduced the dataset reduced to only the trip that took place in New York-Newark-Jersey City, NY-NJ-PA Metropolitan Statistical Area, also known as New York Metropolitan area. The cleaned dataset used in the analysis consisted of a total of 21,618 observations. Further, the data were normalized between 0 and 1 before feeding into the causal discovery algorithms.

**TABLE 1 List of variables**

| S.no. | Variable type          | Variable name        | Description                                                                 | Code                                      | Percentage |
|-------|------------------------|----------------------|-----------------------------------------------------------------------------|-------------------------------------------|------------|
| 1     | Trip characteristic    | Home based           | Generalized purpose of trip, home-based and non-home based                  | \(1\): Home-based trip  \( \eta \)           | 64.9%      |
|       |                        |                      |                                                                            | \(0\): Not a home-based trip \( \eta \)     | 35.1%      |
| 2     | Weekday                | Weekday trip         |                                                                            | \(1\): Yes                               | 69.3%      |
|       |                        |                      |                                                                            | \(0\): No                                | 30.7%      |
| 3     | Distance               | Trip distance in miles, derived from route geometry returned |                                                                            | \(1\): Trip distance less than a mile \( \eta \) | 36.1%      |
|       |                        |                      |                                                                            | \(2\): Trip distance greater than equal to one mile and less than 5 miles \( \eta \) | 46.8%      |
|       |                        |                      |                                                                            | \(3\): Trip distance greater than equal to 5 miles and less than 20 miles \( \eta \) | 15.8%      |
|       |                        |                      |                                                                            | \(4\): Trip distance greater than equal to 20 miles and less than 50 miles \( \eta \) | 1.1%       |
|       |                        |                      |                                                                            | \(5\): Trip distance greater than or equal to 50 miles \( \eta \) | 0.2%       |
| 4     | Peak hour              |                      |                                                                            | \(1\): Yes                               | 42.3%      |
### Trip attributes

| Place type | Household's urban area classification, based on home address and 2014 TIGER/Line Shapefile |
|------------|------------------------------------------------------------------------------------------|
| 1: Urban area | 87.8% |
| 2: Urban cluster | 3.4% |
| 3: Area surrounded by urban areas or not in urban area | 8.8% |

### Gas price

| Price of gasoline, in cents, on respondent's travel day | 1: Less than 250 cents | 2: Greater than 250 cents |
|----------------------------------------------------------|-------------------------|----------------------------|
| 1 | 64.8% | 35.2% |

### Socio-Demographic Information

| Race | Race of household respondent |
|------|------------------------------|
| 1: White | 83.7% |
| 0: Non-White | 16.3% |

| Age | Age of the respondent |
|-----|-----------------------|
| 1: 18-40 | 22.6% |
| 2: 41-65 | 49.1% |
| 3: 65+ | 28.2% |

| Education | Educational Attainment |
|-----------|------------------------|
| 1: Less than a high school graduate | 2.9 |
| 2: High school graduate or GED | 15.0 |
| 3: Some college or associates degree | 21.9 |
| 4: Bachelor's degree | 27.8 |
| 5: Graduate degree or professional degree | 32.4 |

| Gender | Gender |
|--------|--------|
| 1: Male | 46% |
| 0: Female | 54% |

| Worker | Worker status |
|--------|---------------|
| 1: Yes | 58.8% |
| 0: No | 41.2% |

| Household size | Count of household members |
|----------------|----------------------------|
| 1: Only 1 member | 20.3% |
| 2: Two members | 41.3% |
| 3: Three members | 17.7% |
| 4: 4 or more members | 20.6% |

| Vehicle | Count of household vehicles |
|---------|-----------------------------|
| 0: No vehicles | 11.4% |
| 1: One vehicle | 27.6% |
| 2: More than a vehicle | 61.0% |

| Income | Household income |
|--------|------------------|
| 1: Less than $10,000 | 2.5% |
| 2: $10,000 to $49,999 | 20.8% |
| 3: $50,000 to $99,999 | 27.9% |
| 4: $100,000 or more | 48.7% |

| Children | Youngest child in the household is less than 16 years old |
|----------|----------------------------------------------------------|
| 1: Yes | 21.5% |
| 0: No | 78.5% |

| Travel mode | Trip mode is Walking |
|-------------|----------------------|
| 1: Yes | 23.9% |
| 0: No | 76.1% |

| Car | Trip mode is Car/SUV/Van/Pickup truck |
|-----|--------------------------------------|
| 1: Yes | 71.1% |
| 0: No | 28.9% |

| Public | |
|--------||
| 1: Yes | 5.0% |
Trip mode is Public or commuter bus/City-to-city bus/Amtrak or commuter rail/Subway or elevated or light rail or street car 0: No 95.0%

Proposed methodology
In this study, we propose to use a combination of Causal Discovery and SEM to model travel mode choice. Data along with domain knowledge needs to be inputted into the causal discovery algorithms. The output from these algorithms are causal graphs, which can be fed into a SEM model. In this study, the four causal discovery algorithms introduced above are tested (i.e., PC, FCI, FGES, and LiNGAM). The output causal graph from each of the algorithms was inputted to generate a separate SEM model. The results from each of the SEM models were interpreted and compared. Figure 1 illustrates the proposed methodology. The Py-causal (53) and Lingam (54) python libraries were used for causal discovery algorithms, and the semopy (55) library was used for the SEMs.

Previous studies have found that incorporating domain knowledge to the causal discovery algorithms improve their performance (5,16); hence, some graphical restrictions were added to the causal graphs based on the domain expertise. Care was taken to minimize the number of such restrictions and to add only the ones that are obvious. The following domain knowledge restrictions were added:

- The three travel modes (car, public, and walk) were set as the target variable and hence were not allowed to cause any other variables.
- The trip characteristics were not allowed to cause the trip attributes and the socio-demographic variables.
- The trip attributes were assumed not to cause the socio-demographic variables.
- Place type, gas price, race, age, and gender were assumed to be exogenous variables for the scope of this study.
- Education is assumed not to be caused by worker, vehicle, income, and children.

Since several causal discovery algorithms used in this study do not accept latent confounders, the study assumes that travel mode causal structure is not affected by any variable other than those mentioned in Table 1.
RESULTS
As a preliminary analysis, the correlations between the variables were found. Since the variables are ordinal and binary, Spearman rank-order correlation was used. Figure 2 shows the heat map of the correlations between the variables and shows that, except for those between the travel modes, the correlations between the variables are low. Only two correlations stand out: 0.61 between household_size and children, and -0.56 between distance and walk.

Figures 3, 4, 5, and 6 show the output from the SEM models build on PC, FCI, FGES, and LiNGAM algorithms, respectively. The causal structure from LiNGAM is the densest (with 105 edges) while the one from LiNGAM is the least dense (with only 23 edges). We also note that FCI indicated a possibility of some unobserved confounder between a few variables. This was not explored further since it is out of the scope of this study.
Figure 2 Spearman rank-order correlation
Figure 3 Results from PC-based SEM

Figure 4 Results from FCI-based SEM
Figure 5 Results from FGES-based SEM
Results from LiNGAM-based SEM

The SEM models also provide the coefficients and p-values for each of the edges in the causal structure as shown in figures 3-6. Most edges are found to be statistically significant over the 95% confidence interval (p-value < 0.05). Exceptions do occur in PC. The edges from Race to Household_size, Worker to Household_size came out to be statistically insignificant.

Table 2 presents the various SEM model evaluation indices. LiNGAM-based SEM has the lowest values of chi-square while FCI-based SEM has the highest one. LiNGAM-based SEM also produces the highest values of CFI, GFI, AGFI, NFI, and TLI - each above the general accepted level (9,41,51). Further, it gives the least value of RMSEA which is the only one to be within the acceptable range (less than 0.06) (51). In terms of AIC and BIC, LiNGAM-based SEM achieves very low values, greater than only those obtained from FCI-based SEM. The FCI-based SEM performs the worst in all evaluation indices except for AIC and BIC. One explanation for it to obtain the lowest values of AIC and BIC might be that these values capture the comparative level of overfitting (51) which could be true for this model since it produces the least dense graph. It must be noted that, even though, chi-square value was significant in all the model (p > 0.05), it could be perhaps due to the large size of the study dataset (51).

Table 3 shows the detailed result from LiNGAM-based SEM model to offer further insights.

**TABLE 2 Model evaluation indices for SEM models based on the various causal discovery algorithms**

|                        | PC-based | FCI-based | FGES-based | LiNGAM-based |
|------------------------|----------|-----------|------------|--------------|
| Chi-squared test       | 19817    | 85983     | 12261      | 2398         |
| p-value for Chi-squared test | 0.00     | 0.00      | 0.00       | 0.00         |
| Chi-squared test Baseline | 286915   | 284548    | 284548     | 287473       |
| Comparative fit index (CFI) | 0.93     | 0.70      | 0.96       | 0.99         |
| Goodness-of-fit index (GFI) | 0.93     | 0.70      | 0.96       | 0.99         |
| Adjusted goodness-of-fit index (AGFI) | 0.91     | 0.63      | 0.94       | 0.98         |
| Normed fit index (NFI)  | 0.93     | 0.70      | 0.96       | 0.99         |
| Tucker-Lewis index (TLI) | 0.91     | 0.63      | 0.94       | 0.98         |
| Root Mean Square Error of Approximation (RMSEA) | 0.093    | 0.198     | 0.082      | 0.045        |
### TABLE 3 Modeling results from LiNGAM-based SEM

| lval | rop | rval                  | Estimate | Std. Err | p-value |
|------|-----|-----------------------|----------|----------|---------|
| 0    | Home_based | ~                    | Place_type | -0.05    | 0.00    | 0.00    |
| 1    | Home_based | ~                    | Gas_price  | -0.03    | 0.00    | 0.00    |
| 2    | Home_based | ~                    | Education  | -0.07    | 0.00    | 0.00    |
| 3    | Home_based | ~                    | Gender     | 0.04     | 0.00    | 0.00    |
| 4    | Home_based | ~                    | Worker     | -0.06    | 0.00    | 0.00    |
| 5    | Home_based | ~                | Household_size  | 0.09     | 0.00    | 0.00    |
| 6    | Weekday   | ~                    | Home_based  | -0.07    | 0.00    | 0.00    |
| 7    | Weekday   | ~                    | Race       | -0.05    | 0.00    | 0.00    |
| 8    | Weekday   | ~                    | Age        | 0.04     | 0.00    | 0.00    |
| 9    | Weekday   | ~                    | Education  | 0.04     | 0.00    | 0.00    |
| 10   | Weekday   | ~                    | Gender     | -0.03    | 0.00    | 0.00    |
| 11   | Weekday   | ~                    | Worker     | -0.09    | 0.00    | 0.00    |
| 12   | Weekday   | ~                | Household_size  | -0.03    | 0.00    | 0.00    |
| 13   | Weekday   | ~                    | Income     | -0.02    | 0.00    | 0.00    |
| 14   | Weekday   | ~                    | Children   | 0.05     | 0.00    | 0.00    |
| 15   | Distance  | ~                    | Home_based  | 0.19     | 0.00    | 0.00    |
| 16   | Distance  | ~                    | Peak_hour  | 0.06     | 0.00    | 0.00    |
| 17   | Distance  | ~                    | Place_type  | 0.17     | 0.00    | 0.00    |
| 18   | Distance  | ~                    | Gas_price  | -0.02    | 0.00    | 0.00    |
| 19   | Distance  | ~                    | Race       | -0.41    | 0.00    | 0.00    |
| 20   | Distance  | ~                    | Worker     | -0.10    | 0.00    | 0.00    |
| 21   | Distance  | ~                | Household_size  | -1.70    | 0.00    | 0.00    |
| 22   | Distance  | ~                    | Vehicle    | 1.09     | 0.00    | 0.00    |
| 23   | Distance  | ~                    | Children   | 1.30     | 0.00    | 0.00    |
| 24   | Peak_hour | ~                    | Home_based  | 0.20     | 0.00    | 0.00    |
| 25   | Peak_hour | ~                    | Weekday    | 0.17     | 0.00    | 0.00    |
| 26   | Peak_hour | ~                    | Worker     | 0.15     | 0.00    | 0.00    |
| 27   | Peak_hour | ~                | Household_size  | 0.02     | 0.00    | 0.00    |
| 28   | Peak_hour | ~                    | Children   | 0.04     | 0.00    | 0.00    |
| 29   | Education | ~                    | Race       | 0.14     | 0.00    | 0.00    |
| 30   | Education | ~                    | Age        | -0.11    | 0.00    | 0.00    |
| 31   | Education | ~                    | Gender     | -0.05    | 0.00    | 0.00    |
| 32   | Worker    | ~                    | Race       | 0.07     | 0.00    | 0.00    |
| 33   | Worker    | ~                    | Age        | -0.58    | 0.00    | 0.00    |
| 34   | Worker    | ~                | Education  | 0.21     | 0.00    | 0.00    |
| 35   | Worker    | ~                    | Gender     | 0.12     | 0.00    | 0.00    |
| 36   | Household_size   | ~                | Race       | -0.03    | 0.00    | 0.00    |
|   | Variable 1          | Variable 2          | Beta 1   | Beta 2   | Beta 3   |
|---|---------------------|---------------------|----------|----------|----------|
| 37| Household_size      | ~                   | 0.07     | 0.00     | 0.00     |
| 38| Household_size      | ~                   | -0.09    | 0.00     | 0.00     |
| 39| Household_size      | ~                   | 0.04     | 0.00     | 0.00     |
| 40| Household_size      | ~                   | -0.08    | 0.00     | 0.00     |
| 41| Household_size      | ~                   | 0.25     | 0.00     | 0.00     |
| 42| Household_size      | ~                   | 0.90     | 0.00     | 0.00     |
| 43| Vehicle             | ~                   | 0.33     | 0.00     | 0.00     |
| 44| Vehicle             | ~                   | 0.04     | 0.00     | 0.00     |
| 45| Vehicle             | ~                   | -0.01    | 0.00     | 0.00     |
| 46| Vehicle             | ~                   | 0.00     | 0.00     | 0.00     |
| 47| Vehicle             | ~                   | 0.12     | 0.00     | 0.00     |
| 48| Vehicle             | ~ Household_size    | 1.53     | 0.00     | 0.00     |
| 49| Vehicle             | ~ Income            | 0.10     | 0.00     | 0.00     |
| 50| Vehicle             | ~ Children          | -1.17    | 0.00     | 0.00     |
| 51| Income              | ~ Race              | 0.26     | 0.00     | 0.00     |
| 52| Income              | ~ Age               | 0.00     | 0.00     | 0.00     |
| 53| Income              | ~ Education         | 0.33     | 0.00     | 0.00     |
| 54| Income              | ~ Gender            | 0.05     | 0.00     | 0.00     |
| 55| Income              | ~ Worker            | 0.24     | 0.00     | 0.00     |
| 56| Income              | ~ Children          | 0.13     | 0.00     | 0.00     |
| 57| Children            | ~ Race              | 0.01     | 0.00     | 0.00     |
| 58| Children            | ~ Age               | -0.49    | 0.00     | 0.00     |
| 59| Children            | ~ Education         | 0.00     | 0.00     | 0.00     |
| 60| Children            | ~ Gender            | -0.01    | 0.00     | 0.00     |
| 61| Children            | ~ Worker            | 0.06     | 0.00     | 0.00     |
| 62| Walk                | ~ Home_based        | 0.16     | 0.00     | 0.00     |
| 63| Walk                | ~ Weekday           | -0.01    | 0.00     | 0.00     |
| 64| Walk                | ~ Distance          | -1.07    | 0.00     | 0.00     |
| 65| Walk                | ~ Peak_hour         | 0.02     | 0.00     | 0.00     |
| 66| Walk                | ~ Place_type        | 0.20     | 0.00     | 0.00     |
| 67| Walk                | ~ Gas_price         | -0.04    | 0.00     | 0.00     |
| 68| Walk                | ~ Race              | -0.36    | 0.00     | 0.00     |
| 69| Walk                | ~ Age               | -0.11    | 0.00     | 0.00     |
| 70| Walk                | ~ Education         | 0.01     | 0.00     | 0.00     |
| 71| Walk                | ~ Gender            | 0.03     | 0.00     | 0.00     |
| 72| Walk                | ~ Worker            | -0.09    | 0.00     | 0.00     |
| 73| Walk                | ~ Household_size    | -1.37    | 0.00     | 0.00     |
| 74| Walk                | ~ Vehicle           | 0.54     | 0.00     | 0.00     |
| 75| Walk                | ~ Income            | 0.10     | 0.00     | 0.00     |
| 76| Walk                | ~ Children          | 1.02     | 0.00     | 0.00     |
| 77| Car                 | ~ Home_based        | -0.06    | 0.00     | 0.00     |
| 78| Car                 | ~ Weekday           | -0.08    | 0.00     | 0.00     |
| 79| Car                 | ~ Distance          | 0.21     | 0.00     | 0.00     |
80 Car ~ Peak_hour -0.01 0.00 0.00
81 Car ~ Place_type 0.00 0.00 0.00
82 Car ~ Race -0.27 0.00 0.00
83 Car ~ Age 0.20 0.00 0.00
84 Car ~ Education -0.03 0.00 0.00
85 Car ~ Gender -0.01 0.00 0.00
86 Car ~ Worker -0.20 0.00 0.00
87 Car ~ Household_size -2.03 0.00 0.00
88 Car ~ Vehicle 1.52 0.00 0.00
89 Car ~ Income -0.13 0.00 0.00
90 Car ~ Children 1.75 0.00 0.00
91 Public ~ Home_based -0.09 0.00 0.00
92 Public ~ Weekday 0.12 0.00 0.00
93 Public ~ Distance 0.97 0.00 0.00
94 Public ~ Peak_hour 0.02 0.00 0.00
95 Public ~ Place_type -0.31 0.00 0.00
96 Public ~ Gas_price 0.07 0.00 0.00
97 Public ~ Race 0.60 0.00 0.00
98 Public ~ Age -0.13 0.00 0.00
99 Public ~ Gender -0.04 0.00 0.00
100 Public ~ Worker 0.34 0.00 0.00
101 Public ~ Household_size 3.38 0.00 0.00
102 Public ~ Vehicle -2.20 0.00 0.00
103 Public ~ Income 0.01 0.00 0.00
104 Public ~ Children -2.79 0.00 0.00
105 Education ~ Education 0.97 0.00 0.00
106 Distance ~ Distance 0.59 0.00 0.00
107 Weekday ~ Weekday 0.98 0.00 0.00
108 Vehicle ~ Vehicle 0.22 0.00 0.00
109 Children ~ Children 0.72 0.00 0.00
110 Household_size ~ Household_size 0.16 0.00 0.00
111 Income ~ Income 0.66 0.00 0.00
112 Peak_hour ~ Peak_hour 0.91 0.00 0.00
113 Home_based ~ Home_based 0.98 0.00 0.00
114 Worker ~ Worker 0.61 0.00 0.00
115 Walk ~ Walk 0.16 0.00 0.00
116 Public ~ Public 0.00 0.00 1.00
117 Car ~ Car 0.13 0.00 0.00

**DISCUSSION**
Over recent years, the field of transportation has seen a growing popularity in using advanced techniques, like Machine Learning and Deep Learning (56–61). Introducing the concept of causality in transportation is a step forward. To do so, this study compares four different causal discovery algorithms to model travel
mode choice. The four techniques differ in their assumptions and methodology. These differences are reflected in the causal graphs they produced. These causal graphs varied drastically in terms of their complexity. LiNGAM produced the most complex causal graph with more than four times the number of edges than the graph generated by FCI. The causal graph obtained from FCI was comparatively the simplest. When the SEM models built on each of the four algorithms were compared, we find that overall the LiNGAM-based SEM performed the best while FCI-based SEM performed the worst. The superior performance of the LiNGAM-based SEM supports that the causal graph produced by LiNGAM is more reliable and could be the most accurate among the four.

While all the four algorithms agreed on some of the causal relationships, they also have their differences. No single common variable was found to be a direct cause of choosing private vehicle. This was not the case with public transit and walking. All four algorithms found that both distance and the number of household vehicles have a causal relation with choosing public transit as well as walking. All four SEMs found a positive causal impact of distance and a negative causal impact of the number of household vehicles on choosing public transit. This finding about choosing public transit seems logical.

Unless restricted, the causal discovery algorithms find causal relations between all the variables in the dataset. This could lead to the detection of some of the very complicated causal connections. For instance, all four algorithms found a causal link from race to education, and from race to the number of household vehicles. Further, all four SEM models found a positive coefficient for both of these links, implying that being non-white has a negative causal impact on educational attainment and the number of households vehicles. Studying the impact of race on education and vehicle ownership is beyond the scope of this study.

Since the LiNGAM-based SEM was found to offer the best modeling performance, the rest of this section focuses only on this model. This model identified presence of children in the household, number of household vehicles, distance, age, and place type to have a positive causal impact (in decreasing order of their magnitude) on choosing private vehicle. On the other hand, household size, white race, employment, household income, weekday, home-based trip, education, peak hour, and male to have negative causal relation (in decreasing order of magnitude) on choosing private vehicle.

Similarly, household size, distance, white race, employment, weekday, gas price, peak hour, and household income were found to be positively causing (in decreasing order of their magnitude) the selection of public transport as a mode. In contract, the negative causes (in decreasing order of their magnitude) are presence of children in the household, number of household vehicles, place type, age, home-based trip, and male.

Lastly, the positive causes of choosing to walk (in decreasing order of their magnitude) are presence of children in the household, number of household vehicles, place type, home-based trip, household income, male, peak house, and education. The negative causes of deciding to walk (in decreasing order of their magnitude are) are household size, distance, white race, age, employment, gas price, and weekday. These results seem rational. Among the direct causes of the travel modes, there are only two causal connections which appear to be less convincing. Choosing to walk has a positive causal connection with the number of household vehicles while a negative causal connection with gas price. Though these causal relations may be appropriate in the context of the New York Metropolitan Area.

Overall, the performance recorded suggests that Causal Discovery based SEMs is a dependable methodology. The biggest advantage of this approach is that the SEM would be based on data-driven causal graphs and simple assumptions. Another potential benefit is the possible reduction in the time to estimate SEM. Although unexplored here, we posit that Causal Discovery also has the potential to uncover unobvious relationships specific to local contexts (such as the positive relation from household income to choosing public transportation).

CONCLUSIONS
This study applies four different causal discovery algorithms to study the causal relations related to travel mode choice. The causal graphs obtained from these algorithms varied in their complexity and inferences. The four algorithms found several common causal relations but also had substantial differences. In all, the
algorithms were able to extract the complex relations in the data with the help of some basic domain knowledge. The study proposed and implemented a novel approach of combining Causal Discovery and SEM to model travel mode choice. This is a step forward from the previous usage of SEMs in travel mode choice modeling which relied solely on domain knowledge and literature. Causal Discovery offers SEM a hypothesized causal structure which is grounded in data with only very limited domain knowledge. The combination also benefits Causal Discovery by providing quantitative parameters to the causal links and model evaluation indices. These could be a reliable method for comparing the results of various Causal Discovery experiments. This might be particularly useful in real-world scenarios where the ground truth is usually not known.

In our study, LiNGAM turned out to perform the best. In the comparative analysis, LiNGAM-based SEM achieved the lowest values of chi-square, RMSEA, and greater than 0.95 values of CFI, GFI, AGFI, NFI, and TLI. The implementation of this LiNGAM-based SEM method provided insights to the complex relations in transportation networks. The study identified several variables that have either a positive or negative causal connection with the mode choice decision. These results seem logically reasonable.

The study has also potentials for improvements. The most notable one could be to include latent or unobserved confounding variables. Further, the level-of-service attributes of the different modes were not included in the model due to data limitations. Finally, testing the proposed framework for other mobility choice contexts, for instance residential location, can help to generalize the findings. These improvements can be part of future research.

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AUTHOR CONTRIBUTIONS
The authors confirm contribution to the paper as follows: study conception: RSC, SD, EZ, CFC, and FCP; study design: RSC, CR, SD, EZ, CFC, and FCP; data collection: Not applicable. Used NHTS data; analysis and interpretation of results: RSC, CR, and SA; draft manuscript preparation: RSC, CR, and SA. All authors reviewed the results and approved the final version of the manuscript.
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