Causal Inference on E-Scooter Adoption: A Study on Sociodemographic and Behavioral Factors

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Introduction: Causal Inference in E-Scooter Adoption

- **E-Scooters: A Game Changer**
  - E-scooters have emerged as a key player in transforming urban transportation.
  - They offer a quick, eco-friendly, and convenient alternative to traditional modes of transport."
- **Benefits Highlighted**
  - **Eco-Friendly**: Reducing carbon footprint with zero emissions.
  - **Ease of Use**: Simple to operate, perfect for short urban trips.
  - **Decongesting Cities**: A solution to urban traffic woes, easing congestion.

Problem Description

- **Purpose of the Study:** To understand the factors influencing user behavior and acceptance of shared E-scooters.

Analytical Approaches:

- **Causal Discovery:** Used causal discovery algorithms PC and GES for learning the structure and compared the approaches.
- **Average Causal Effects:** Backdoor approach is used to estimate average treatment effects of different *demographic* variables on intention to use in the future.
- **Structural Equation Modeling (SEM)**: Analyzing patterns and relationships among key *behavioral* variables within the Technology Acceptance Model (TAM).
- **Causal Analysis in Python**: Using Dowhy library to identify direct causal effects and validate findings from SEM.

Objective:

- To combine insights from SEM and causal analysis for a comprehensive understanding of factors driving E-scooter adoption.

Project dataset

Composition:

- Variety of Variables (277 columns)
- Mixed Data Types (Categorical, Numerical, Binary)

Key Variables:

- Demographics: Age, Gender, Race
- Transportation Preferences: Vehicle Ownership, Use of E-scooters
- Geographic Data: IP Address Location

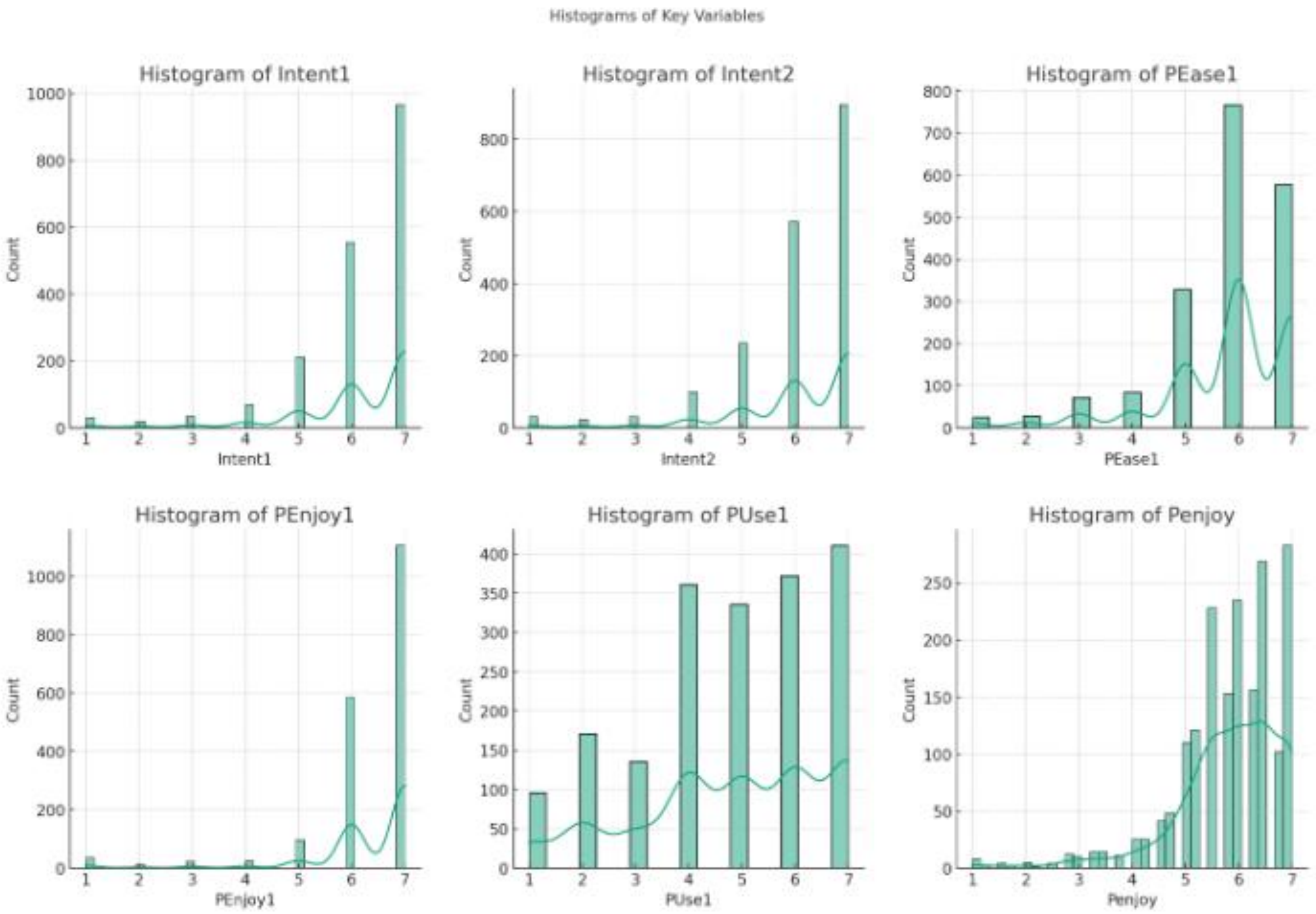
Data Size:

- 2167 Entries
- Broad Coverage Across Multiple Aspects

Purpose:

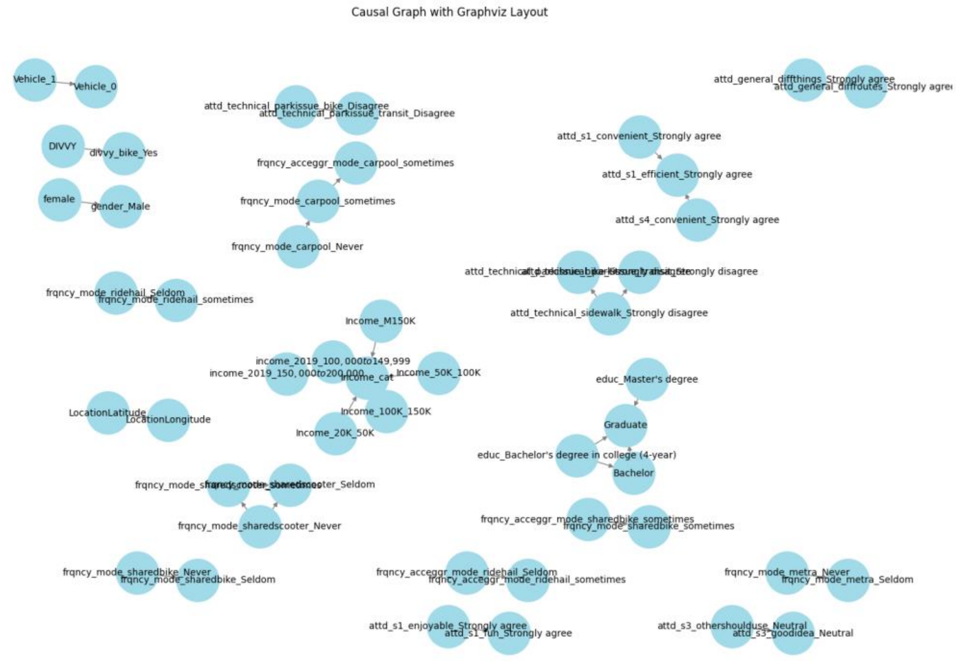
- Understanding Transportation Preferences
- Insights into E-scooter Usage

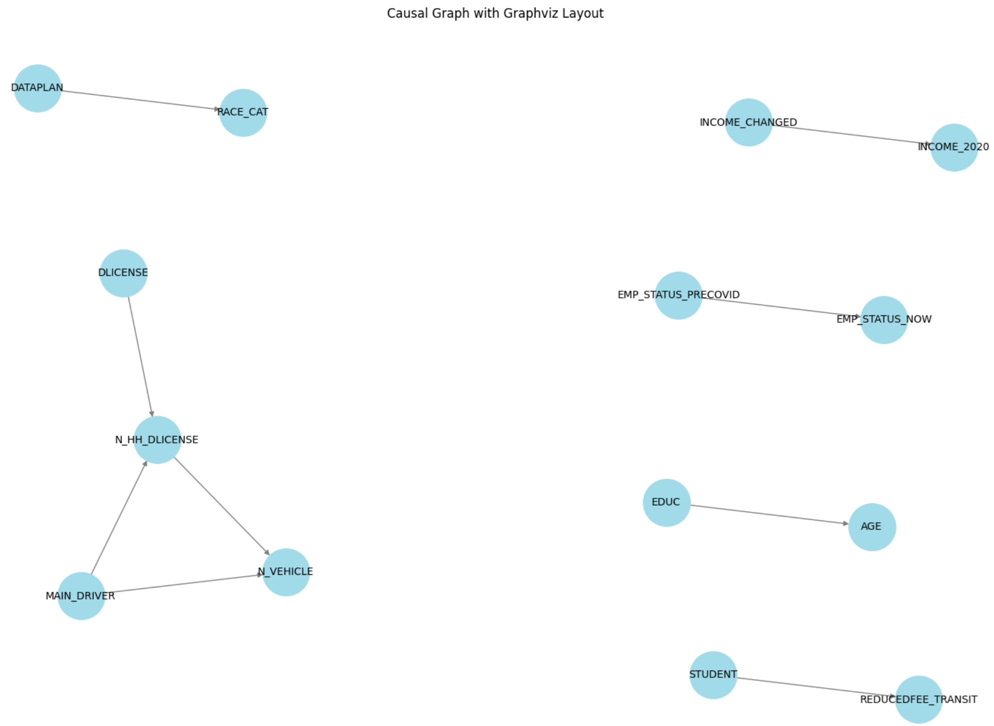
histograms for six key variables from the dataset



Causal Discovery

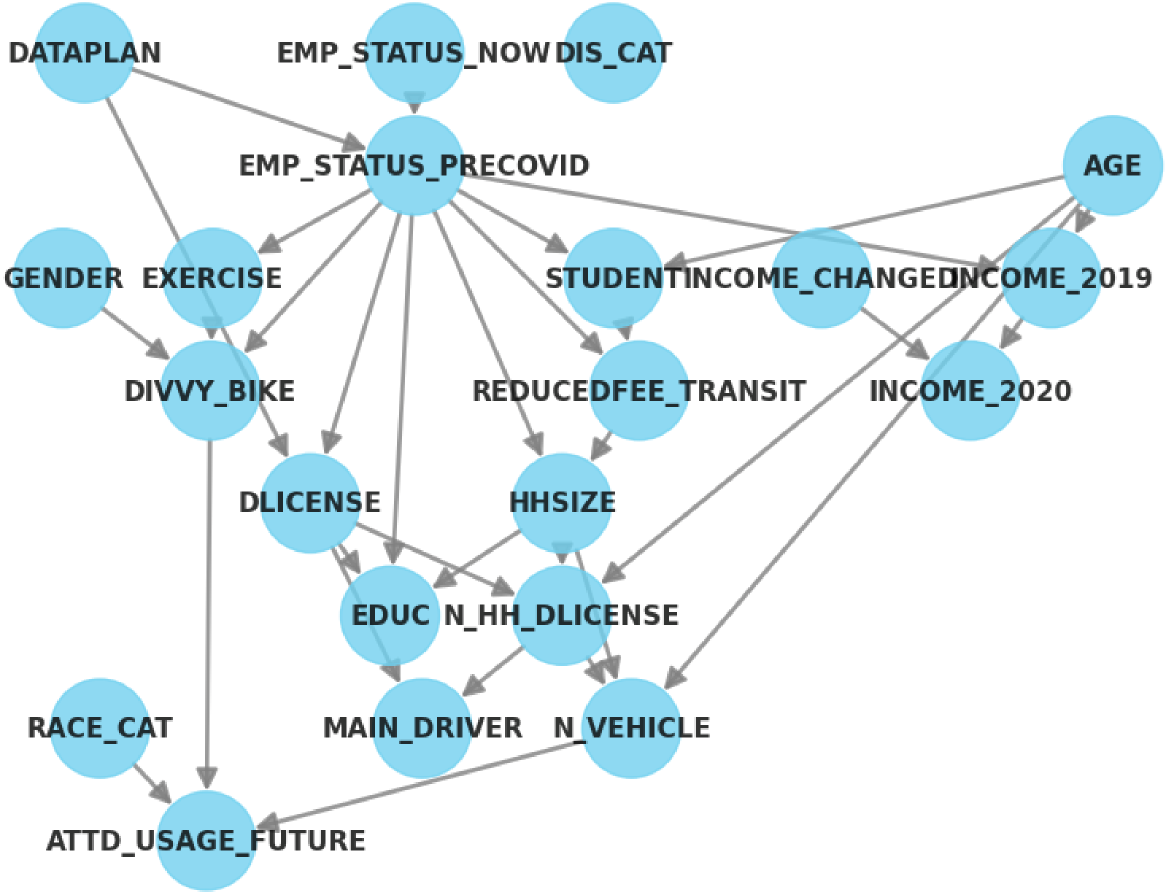
PC Algorithm





Causal Discovery

GES Algorithm



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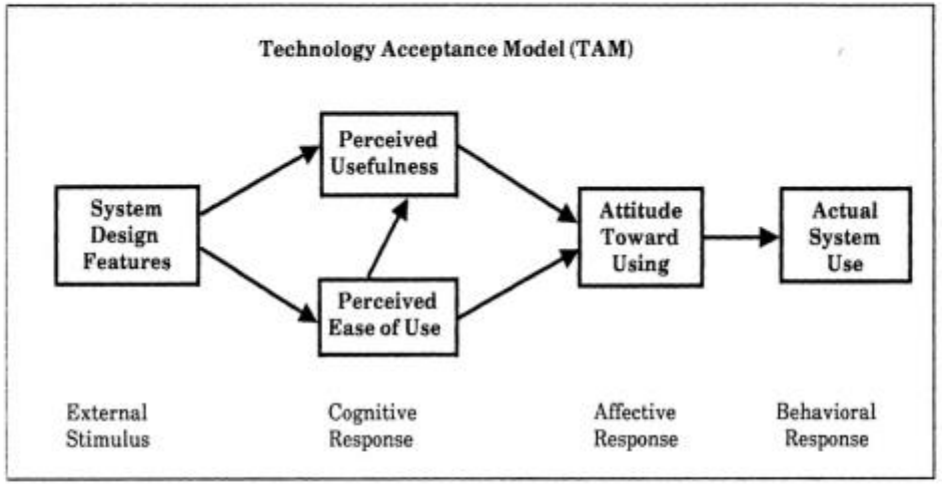
Causal Effects Estimation

Average treatment effects on intention to use in the future

- ATT of Student status : 0.038
- ATT of No of Vehicles : 0.058
- ATT of Exercise : -0.001
- ATT of Race category : 0.023
- ATT of reduce fee transit : 0.10

Understanding the Technology Acceptance Model (TAM) for Behavioral Variables

- **TAM**:
  - Developed by Davis (1989) for understanding technology adoption.
  - Focuses on two main factors: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU).
- **Relevance to E-Scooter Study:**
  - Ideal for assessing factors influencing E-scooter adoption.
  - Widely validated in technology acceptance research.



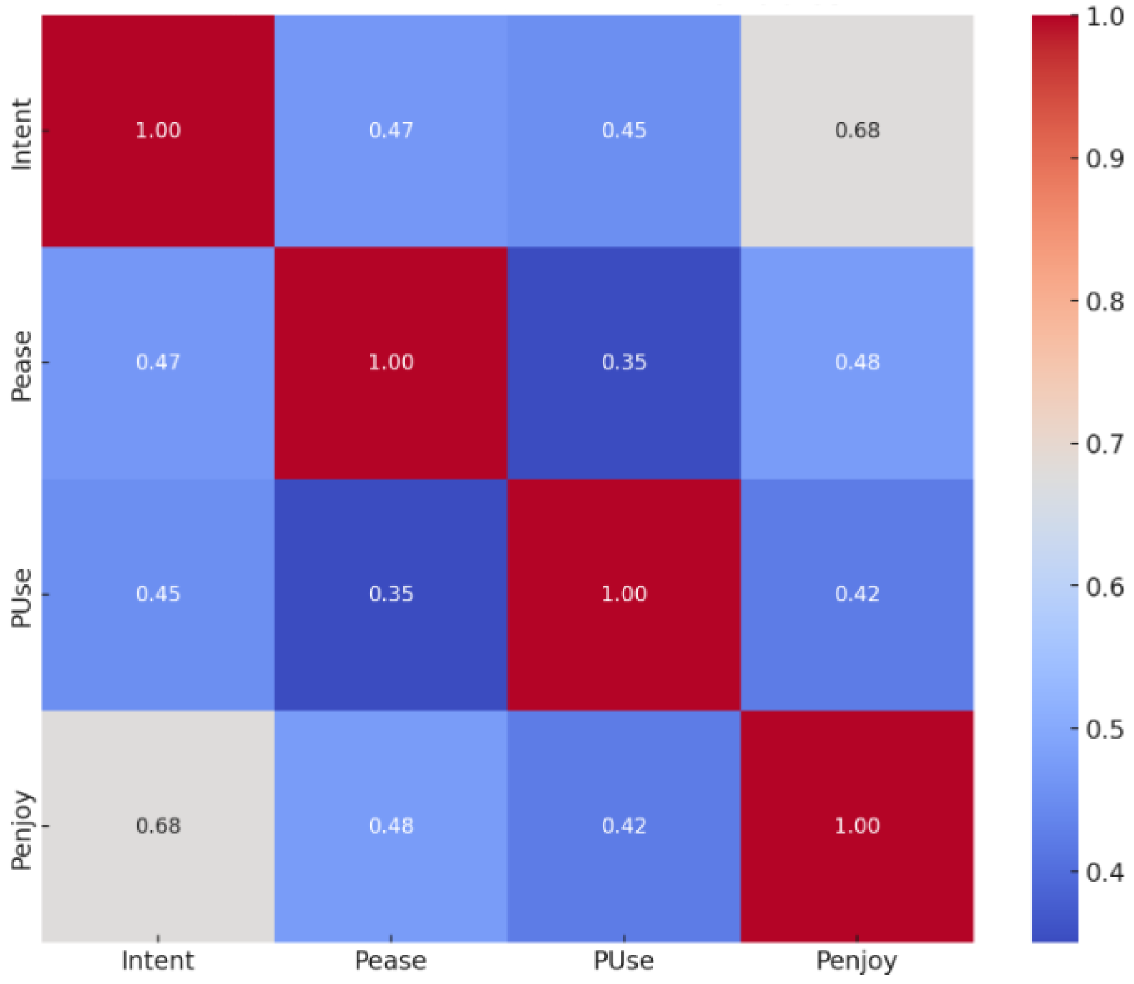
SEM Model (R): Latent variables

- Each latent variable is defined by several observable indicators, like user opinions on E-scooter use.
- The main latent variables in our SEM model, which are critical concepts to extract user's perceptions and preferences.
- Understanding these relationships helps us to analyze user behavior and preferences regarding shared E-scooter usage.

Table: SEM Model - Latent Variables and Indicators

Latent Variable	Indicators
Intent to Use	1. "I intend to continue using shared E-scooters."
	2. "I will recommend others to use shared E-Scooters."
Perceived Ease of Use	1. "E-scooter apps are easy to use and understand."
	2. "Using E-scooters requires little mental effort."
	3. "Using E-scooters requires little physical effort."
Perceived Usefulness	1. "E-scooters are useful for daily transport needs."
	2. "E-scooters make travel more convenient."
	3. "E-scooters make travel more efficient."
Perceived Enjoyment	1. "Using E-scooters is enjoyable."
	2. "Using E-scooters is fun."
	3. "E-scooters rides are memorable and enrich life."
	4. "I feel good about life after riding an E-Scooter."

The correlation heatmap of the relationships between the latent variables in the SEM model:

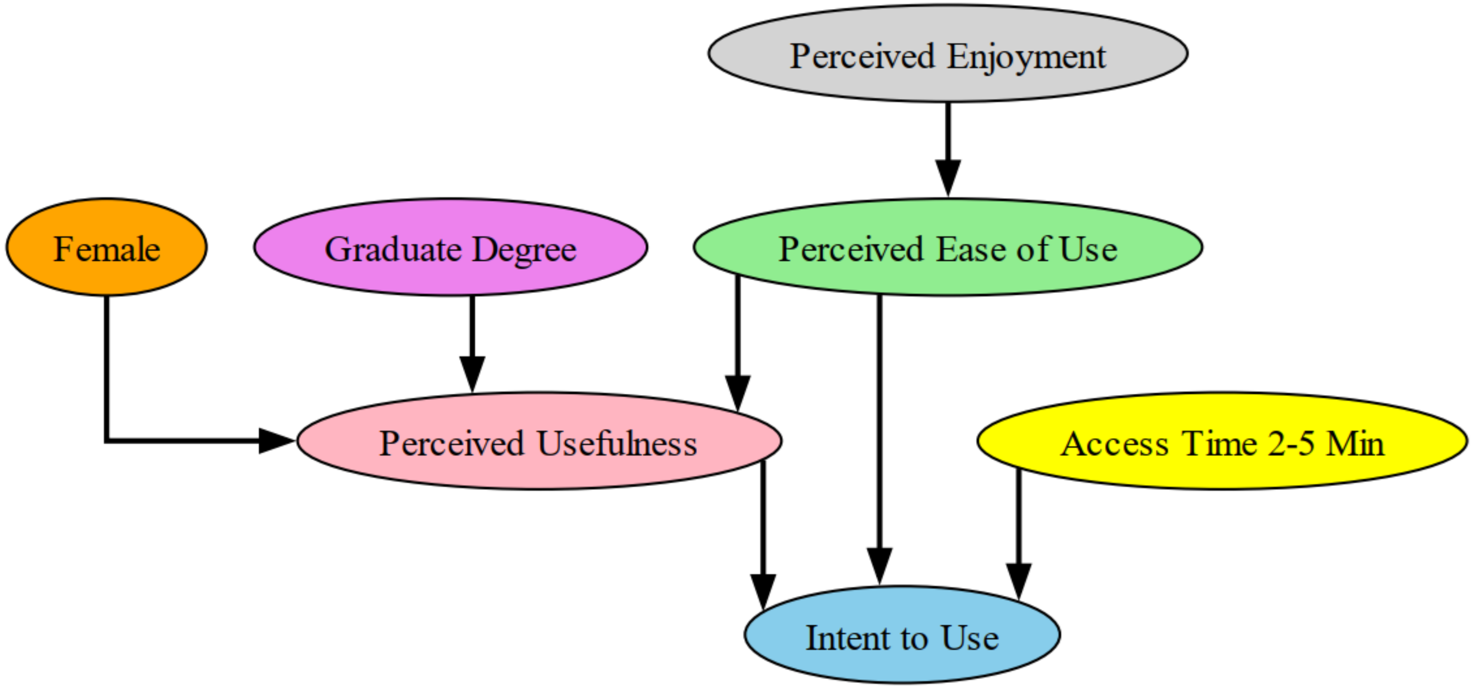


Key Path Coefficients in SEM Analysis

- The path coefficients indicate the strength and significance of relationships between variables.
- This table summarizes the significant path coefficients from the SEM model.
- Estimates indicate the effect size, with positive values showing a direct relationship and negative values indicating an inverse relationship.

Dependent Variable	Predictor	Estimate	P-value
Intent to Use	Perceived Ease of Use	0.734	<0.001
	Perceived Usefulness	0.273	<0.001
	Frequency of Access (2-5 min)	0.202	<0.001
Perceived Usefulness	Perceived Ease of Use	1.001	<0.001
	Female Gender	-0.199	<0.001
	Holding a Graduate Degree	-0.142	0.007
	Frequency of Access (2-5 min)	0.313	<0.001
Perceived Ease of Use	Perceived Enjoyment	0.538	<0.001

SEM Model Results



- Factors influencing the use of e-scooters, highlighting the importance of ease of use, usefulness, and enjoyment as well as gender and education in shaping user intentions.

Enhancing TAM Analysis with Python Causal Analysis

Objective: To complement SEM findings from R with causal analysis using Python and also Validates our SEM.

Causal Insights Sought:

- Direction and Strength: Determines the direct influence and impact of variables like Perceived Ease of Use on Intent to Use.
- Effect Quantification: Measures the magnitude of these influences.

Methodology Overview:

- **Factor Analysis:** Construct latent variables from observed data.
- **Dowhy Causal Modeling:** Employs causal inference techniques to establish direct effects.
- **Refutation Tests:** Includes Random Common Cause, Placebo Treatment, and Data Subset methods to test the robustness of causal findings.

Key Findings from Causal Analysis (Python)

- **Purpose**: Identifying direct causal impacts within TAM using Python's Dowhy library.
- Causal Relationships and Estimates:
- Key Relationships and Estimates:

  Pease → Intent

  PUse → Intent

  Penjoy → Pease

  Pease → PUse

- Influences of Demographic and Contextual Factors:

  Female → PUse

  Graduate Degree → PUse

  Access Time (2-5 min) → Intent

Understanding Refutation Tests in Causal Analysis

- **Purpose of Refutation Tests:** To validate the robustness of causal estimates against potential biases and confounding factors.
- **Types of Refutation Tests:**
  - **Random Common Cause**: Tests for hidden confounders by adding a random variable to the model. Stability in the causal estimate suggests robustness against unobserved biases.
  - **Placebo Treatment:** Replaces the treatment with a placebo to check if the observed relationship is genuinely causal. A significant reduction in effect when using placebo supports the original causal inference.
  - **Data Subset Refutation**: Re-estimates the causal effect using a subset of the data to test consistency. Consistent effects across subsets reinforce the reliability of the findings.
- **Role in Causal Inference:**
  - These tests act as rigorous checks, ensuring that the causal relationships identified are not merely correlations or results of hidden biases.

Causal Relationships Involving Perceived Factors

- **Perceived ease of use → Intent**:

  Causal Estimate: 0.2122

  Refutation Tests: Consistent effects across tests.

- **Perceived usefulness → Intent:**

  Causal Estimate: 0.5098

  Refutation Tests: Robust against various tests.

- **Perceived enjoyment → Perceived ease of use:**

  Causal Estimate: 0.4391

  Refutation Tests: Effect remains stable; significantly reduced in placebo.

❑ **These results suggest that the ease of use, usefulness, and enjoyment have significant and positive causal impacts on user intentions**.

Summary of Causal Analysis Results using Dowhy

- Causal Estimate: The estimated effect of the treatment on the outcome.
- Random Common Cause Effect: Effect after adding a random common cause (tests for hidden confounders).
- Placebo Treatment Effect: Effect after using a placebo treatment (tests if the observed relationship is likely due to the treatment).
- Data Subset Effect: Effect when using a subset of the data (tests consistency of the estimated causal effect).

Relationship	Causal Estimate	Random Common Cause Effect	Placebo Treatment Effect	Data Subset Effect
Pease → Intent	0.2122	0.2123	0.0014	0.2117
PUse → Intent	0.5098	0.5099	-0.00016	0.5074
Penjoy → Pease	0.4391	0.4392	-0.0046	0.4396
Pease → PUse	0.4047	0.4046	-0.0037	0.4053
Female → PUse	0.1194	0.1194	-0.0025	0.1194
Graduate Degree → PUse	0.1067	0.1069	-0.0026	0.1058
frqncy_access_2_5_min → Intent	-0.1731	-0.1730	-0.0065	-0.1745

Conclusions

- **Causal Discovery:**
  - Identified causal structure from observational data using GES algorithm. This structure is further used to estimate causal effects of different variables.
- **SEM Insights:**
  - Identified strong correlations among key TAM variables in the e-scooter context.
- **Causal Analysis Findings:**
  - Positive direct effects of perceived factors on user intent.
- SEM and causal analysis offer a comprehensive view of user behavior towards E-scooters.
- The importance of perceived factors and reveal complex demographic influences, guiding strategies for E-scooter adoption and user experience enhancement.

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Thank you