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COMPARING NETWORK REPRESENTATIONS OF U.S. VEHICLE CUSTOMER PREFERENCES: A CASE STUDY OF EV CONSIDERATION AND PURCHASE BEHAVIOR

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ABSTRACT

Modeling customer preferences in heterogeneous markets remains challenging because choices are shaped simultaneously by product characteristics, overlapping consideration sets, and social context. This study develops a data-driven framework for customer preference modeling using multiple network representations of increasing dimensionality and demonstrates it through a case study of EV consideration and purchase behavior in the U.S. vehicle market. Integrating new-car buyer survey data, vehicle attribute data, and customer-reported social-network information, the study compares three buyer segments: non-EV buyers, non-EV buyers who considered EVs, and EV buyers. The key contribution is a systematic comparison of unidimensional, bipartite, and multidimensional networks within the same EV preference setting, showing how each representation reveals different aspects of market structure. Within the analyzed dataset, EV consideration and purchase were more strongly associated with powertrain-related vehicle attributes than with baseline demographics. Across network representations, the three buyer groups exhibit distinct structures: non-EV buyers remain broad and anchored by traditional vehicles, non-EV buyers who considered EVs are the most structurally heterogeneous and occupy an intermediate position between non-EV-only and EV-purchasing segments, and EV buyers are the most concentrated around a narrow EV-centered core. The findings show that increasing network dimensionality does not simply add detail, but changes what becomes visible about the market—from product-level competition, to customer-level decision sets, and to socially embedded ownership structure. These results demonstrate the value of multi-representation network modeling in identifying associations and structural patterns in heterogeneous EV consideration and purchase behavior.

Keywords: U.S. Vehicle Market, Electric Vehicles, Customer Preferences, Data Visualization, Network Modeling.

1 INTRODUCTION

As shown in Figure 1, the global vehicle market has undergone a significant structural shift over the past decade, driven by the rapid growth of electric vehicles (EVs). In 2024, global electric car sales exceeded 17 million, representing more than 20% of new passenger car sales worldwide [1]. This growth trajectory highlights a fundamental transition in the automotive industry, where EVs are no longer a niche technology, but a central component of the modern vehicle market. A similar trend has been observed in the United States, where the adoption of EVs has accelerated in recent years. U.S. EV sales increased from well below 2% of new vehicle sales in the late 2010s to more than 10% of the total light-duty vehicle sales in 2024 [1]. Although traditional vehicles continue to constitute the majority of the market in absolute volume, the rapid expansion of EV sales has begun to

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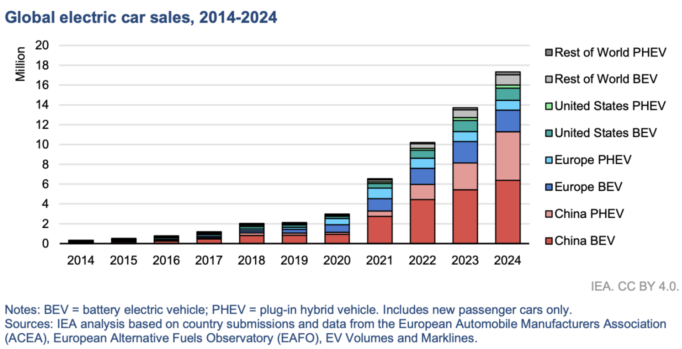

FIGURE 1: Growth of electric vehicle sales in the U.S. and globally over the past decade (data source: [1]). In this study, following prior definitions [2], we classify vehicles based on whether they could be charged from the electric grid. "EV" denotes battery-electric vehicles (BEVs); "Plug-In" denotes plug-in hybrid electric vehicles (PHEVs); "Hydrogen" denotes fuel-cell electric vehicles (FCEVs); and "Traditional" denotes non-plug-in vehicles including gasoline/diesel ICEVs and non-plug-in hybrids (e.g., HEVs and mild hybrids) whose batteries are charged via the engine and regenerative braking rather than from the grid.

influence vehicle design strategies, manufacturing investments, charging infrastructure development, and public policies.

Despite strong aggregate growth, the adoption of EVs remains highly heterogeneous. Customers differ in terms of the vehicles they consider, the attribute trade-offs they prioritize (e.g., purchase price, operating cost, driving range, and charging access), and how social context and information exposure shape their final purchases [3]. Importantly, these decisions do not occur in isolation: vehicles compete through overlapping customer consideration sets, and preferences can be shaped by interpersonal influence and information diffusion. Consequently, market outcomes emerge from coupled interactions among customers, products, and social environments rather than independent, one-shot choices [4–6].

A large body of research explains EV adoption using behavioral and economic decision-making frameworks, most commonly the Theory of Planned Behavior (TPB) and rational choice perspectives [7–11]. Across studies, adoption outcomes are typically associated with (i) attitudes toward expected outcomes, (ii) perceived behavioral control, such as affordability and feasibility of daily use, and (iii) subjective norms reflecting perceived expectations from peers [11, 12]. Empirical findings consistently identify purchase price and total cost considerations, driving range, charging availability, and performance attributes as key drivers of EV consideration and purchase behavior [7, 10, 13–15]. A complementary stream emphasizes values and beliefs (e.g., pro-environmental attitudes and perceived environmental benefits) [16, 17], while also documenting an attitude-behavior gap in which favorable environmental beliefs do not reliably translate into adoption [10, 18, 19]. This gap is often attributed to competing priorities and uncertainty about real-world usability, including charging convenience and everyday mobility constraints [7, 18, 20]. Together, prior work strongly suggests that EV adoption is shaped by both attribute trade-offs and social context. Methodologically, however, much of the literature relies on regression, discrete choice models, or intention-based survey frameworks that treat consumers as largely independent decision-makers [7, 13, 15, 21]. Social influence is commonly acknowledged, but it is often operationalized via aggregated proxies (e.g., perceived norms or neighborhood averages) rather than being modeled explicitly as a relational structure connecting customers and products [12, 22]. As a result, conventional approaches provide limited insight into how co-consideration patterns among vehicles, heterogeneity across customers, and interpersonal connections jointly structure market competition and adoption outcomes.

Network representations address this limitation by directly modeling the relationships among entities [5, 6, 23]. These representations include unidimensional vehicle co-consideration networks, bipartite customer–vehicle networks with consideration and purchase links, and multidimensional networks that simultaneously capture connections such as customer–customer social ties, customer–vehicle purchase relations, and vehicle–vehicle associations [23, 24]. This family of representations has been used to study customer–product systems, including co-consideration behavior and competition structure; however, important gaps remain. Existing network-based studies typically adopt a single representation, such as a unidimensional vehicle competition network or a multidimensional preference network. Consequently, comparatively little work systematically evaluates how analytical conclusions change as network dimensionality increases, or what information is gained or lost when moving from vehicle-only networks to customer–vehicle and socially embedded representations [23, 24]. In addition, social influence is frequently represented using inferred or simulated customer–customer ties (e.g., constructed from demographic or attitudinal similarity) rather than observed social connections, which can blur the distinction between homophily and interpersonal influence and may distort the relational pathways through which information and preferences propagate [25]. Together, these gaps limit our ability to assess how representation choices shape inference about competition structure and heterogeneous EV consideration and purchase patterns, motivating a systematic comparison of network models with different dimensional structures.

This study addresses these gaps by developing a data-driven customer preference modeling framework that integrates complex networks with different dimensions. We demonstrate the framework using a new-car buyer survey dataset that directly measures both consideration sets and customer-centered social contexts. Specifically, the survey records each buyer's considered vehicle models (up to five), the final purchased model (one), demographic characteristics, and a customer social-network (up to ten social contacts), including “who-knows-who” connections among the listed people. The survey also records purchase information within the social-network (i.e., whether a buyer’s social contacts purchased specific vehicle models), enabling an explicit representation of social exposure related to vehicle choice. We merged these survey records with a vehicle attribute dataset and performed data processing steps, including cleaning, standardization, filtering, and merging, along with exploratory visualizations (distributions and correlations) to characterize both customer and vehicle attributes.

Building on these data, we developed and compared three network representations of the customer–vehicle market system: (1) a *unidimensional co-consideration network* in which nodes are vehicle models and an edge indicates that two models are co-considered by at least one customer; (2) a *bipartite customer–vehicle network* with customer nodes and vehicle-model nodes, where one type of customer–vehicle link indicates consideration and a distinct set of links indicates purchase; and (3) a *multidimensional network* integrating (a) people nodes (customers and their social contacts), (b) vehicle model nodes, and (c) multiple relation types, including person-person “knowing” ties (from the “who-knows-who” survey responses) and person-vehicle purchase ties (purchases by customers and by their social contacts as reported in the survey). For each representation, we conducted network analysis and visualization (e.g., degree distributions, density, clustering/transitivity, and community structure) to characterize the competition structure and customer heterogeneity across different modeling granularities. In particular, we categorize buyers into three behaviorally grounded segments based on their self-reported survey responses: (1) *non-EV buyers*: buyers who only consider traditional vehicles and purchase a traditional vehicle; (2) *non-EV buyers who considered EVs*: buyers whose consideration set includes both traditional vehicles and EVs but who ultimately purchase a traditional vehicle; and (3) *EV buyers*: buyers who only consider EVs and purchase an EV. These segments allow us to connect network structure to heterogeneous EV consideration and purchase outcomes and to examine whether different representations highlight different structural patterns across buyer types. The main **research questions** addressed are: (1) RQ1: What are the differences among customer groups with varying EV consideration and purchase behaviors? (2) RQ2: What information is captured by network representations with different dimensions (unidimensional, bipartite, and multidimensional)?

The remainder of the paper is organized as follows. Section 2 describes the proposed research framework and associated measurements. Section 3 introduces the case study and presents the results across representations and customer segments, followed by a discussion (Section 4) and conclusions (Section 5).

2 RESEARCH FRAMEWORK

Figure 2 summarizes the proposed data-driven customer preference modeling framework. The framework integrates two complementary components. First, an attribute-level analysis is conducted to characterize how product specifications and customer characteristics relate to consideration and choice outcomes (Steps 1–3). Second, a network modeling component constructs complex network representations at multiple levels of dimensionality (Steps 4–6). Rather than treating products and customers as independent observations, this component conceptualizes the vehicle market as an interconnected system in which attribute-based tradeoffs are jointly shaped by relational structures, such as co-consideration among products and social exposure among individuals. This combined approach is designed for markets where customer choices reflect both trade-offs among observable attributes and the structure of attention, exposure, and competition within the market. Details of each step are provided below.

2.1 Step 1 - Data sources and inputs

The first step is to identify the data required to represent a market as both an attribute space and relational system. The framework requires two complementary inputs: (1) behavioral records, encompassing consideration and choice information that identifies which competing alternatives each customer evaluated and ultimately selected, and (2) product attributes, capturing the design and positioning variables (e.g., vehicle price, size, and fuel economy) that drive customers’ trade-offs. Behavioral data are typically sourced from existing stated-response surveys or revealed preference records. Product specifications can be compiled from technical databases and standardized catalogs. In addition, customer characteristics and context variables, such as demographics, stated preferences, and social-context indicators, are incorporated to enable network representations that include customer heterogeneity and interpersonal exposure.

2.2 Step 2 - Data preprocessing and integration

The second step transforms raw customer and product data into a consistent analytic dataset suitable for both attribute-based analysis and relational modeling. This process typically includes cleaning the data by resolving free-text entries, correcting obvious misspellings, and harmonizing naming conventions. For example, customer-reported product names may appear in slightly different forms due to abbreviations, spacing, punctuation, capitalization, or incomplete text; therefore, these entries must be normalized before reliable matching is possible. The preprocessing stage may also include removing administrative or non-analytic fields, checking for duplicate records, and excluding observations with implausible or internally inconsistent data. Next, a unified identifier is constructed to enable a reliable link between alternative products reported by customers and the product spec-

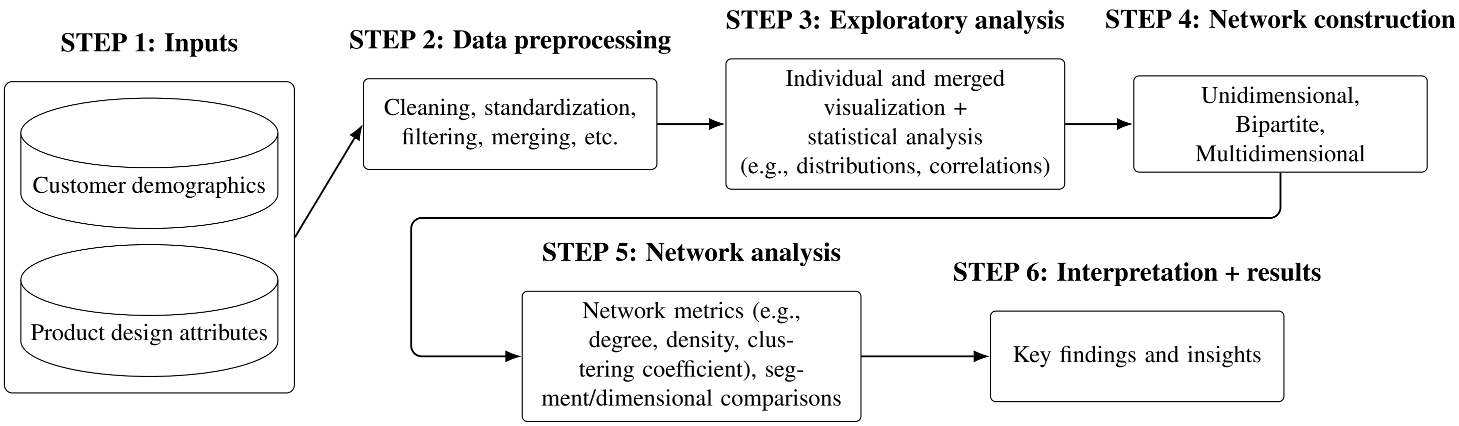

FIGURE 2: Overview of the data-driven customer preference modeling framework, showing how customer and product inputs are transformed through data processing, network construction, network analysis, and interpretation across multiple dimensions.

ification database. In practice, this identifier is a standardized key built from the product attributes most necessary for matching, such as year, make, and model in a vehicle-market application, or brand, model, and product generation in other settings. Once standardized identifiers are established, the customer and product tables are merged so that the observed consideration and choice outcomes can be connected to the corresponding product attributes. Records that cannot be linked because of incomplete information, unmatched product names, or missing product coverage in the reference database are either excluded or handled through an explicit missing-coverage strategy, such as retaining them with missing attribute fields or imputing missing values using methods such as mean or regression-based imputation. Finally, customers are partitioned into behaviorally meaningful segments (e.g., based on consideration and purchase outcomes) to support subgroup comparisons in downstream statistical analysis and network construction.

2.3 Step 3 - Exploratory visualization and statistical association analysis

Step 3 characterizes patterns in product attributes and customer behavior using visualization and statistical association measures. To quantify the correlations among variables with different measurement scales, we applied association measures based on the variable type. For continuous-continuous pairs (e.g., vehicle price, power, fuel economy), we used Pearson's correlation coefficient [26]. For categorical-categorical pairs (e.g., product class, market segment, customer-group outcomes, and demographic categories), we use Cramér's V based on the contingency-table chi-squared statistic [27]. For categorical-continuous pairs (e.g., relationships between product class or segmentation and variables such as price or fuel economy), we use the correlation ratio (η), which compares between-group variation to total variation [28]. Detailed mathematical formulations of these metrics are provided in Appendix A. Collectively, these analyses establish a consistent, mixed-type baseline for interpreting segment differences in the product attribute space and motivate the subsequent relational modeling steps.

2.4 Step 4 - Network construction

Network models provide a flexible way to represent customer–product relations at different levels of structural detail. Prior work in customer preference and product competition modeling has explored multiple network representations, including unidimensional, bipartite, and multidimensional structures, to capture how market outcomes emerge from interdependent relations rather than isolated observations [5, 6, 23, 25, 29, 30]. In Step 4, the integrated dataset is converted into network representations. As shown in Figure 3, depending on the dimension, nodes may include products, customers, and, when available, social-context entities; edges encode observed relations such as co-consideration, consideration, purchase, or social ties. In particular, (1) a *unidimensional (product co-consideration) network* summarizes competition or association among products using aggregated customer attention. Nodes represent products, and an undirected edge between two products indicates that they were co-considered by at least one customer, consistent with co-consideration competition networks in previous studies [29, 30]. (2) A *bipartite (customer–product) network* preserves disaggregated interactions by modeling customers and products as distinct node sets, with edges connecting a customer to each alternative they considered and/or purchased [6, 31, 32]. Compared with unidimensional projections, the bipartite form retains which customers link to which products, enabling analysis of heterogeneous consideration sets and allowing consideration-stage and purchase-stage relations to be distinguished when those edge

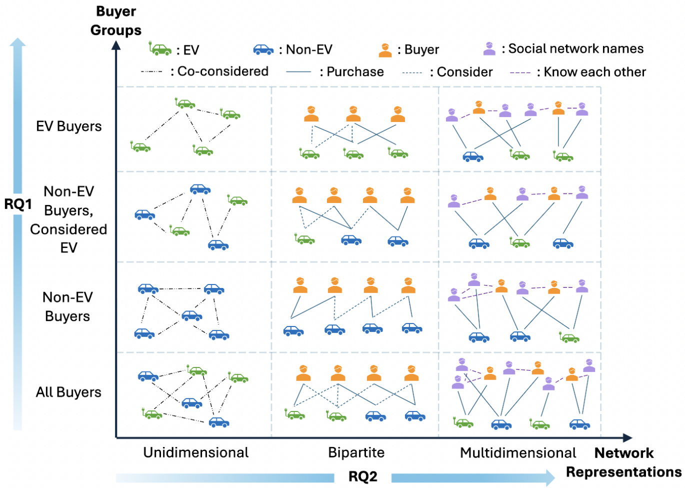

FIGURE 3: Overview of the network analysis workflow across representations and customer groups.

types are encoded separately. (3) A *multidimensional (multilayer) network* integrates multiple node and edge types simultaneously, allowing customer–product relations to be studied together with additional relational contexts such as customer–customer social ties or social-network entities [23, 25]. This representation is used when preserving multiple relation types is necessary to examine how product associations and social context jointly structure observed behavior. Together, these constructions provide complementary encodings of the same underlying market system, ranging from aggregated product-level competition to customer-level interactions and socially embedded ownership structure.

2.5 Step 5 - Network analysis and segment-level comparison

Step 5 evaluates the constructed networks with respect to two complementary research questions. First, holding the network representation fixed, network measures are compared across customer segments to examine how differences in consideration and purchase behavior are reflected in relational market structure. Second, holding the customer segment fixed, network measures are compared across unidimensional, bipartite, and multidimensional representations to evaluate how dimensionality changes the information retained by the model. This comparison helps identify the extent to which higher-dimensional representations preserve, enrich, or transform information about market relationships. To systematically compare the structures, we used measures such as degree, density, clustering coefficient, giant-component percentage, average path length, and betweenness centrality. These measures capture different aspects of relational organization, and their interpretation depends on the representation being analyzed. Appendix B summarizes the measurements used in this study, along with their definitions and interpretations for market analysis.

2.6 Step 6 - Interpretation and study outputs

The final step synthesizes findings from attribute-based analysis and network analysis to interpret behavioral differences across customer groups and to evaluate what is gained or lost as network dimensionality increases. The results connect observed customer segment differences to both product attributes and relational structure, providing insight into how product consideration and purchase outcomes emerge from combinations of trade-offs, shared associations among products, and social-context effects. This synthesis directly supports the study's objectives: understanding heterogeneity in customer behavior and assessing how unidimensional, bipartite, and multidimensional network representations provide complementary perspectives on the product market system.

3 CASE STUDY

This section applies the proposed framework to the U.S. vehicle market case study to address the two aforementioned research questions, with particular emphasis on electrified powertrains and observed patterns of EV consideration and purchase behavior.

3.1 Step 1 - Data sources and inputs

In this study, we use two primary datasets: a new-car buyer survey dataset and a vehicle attribute dataset. The survey dataset was collected as part of our previous research project through an egocentric survey administered by Qualtrics. The survey was launched on March 6, 2023 and conducted through June 26, 2023, targeting new-car buyers across the United States who reported purchasing a new vehicle within the previous 12 months. The final survey sample includes 2,283 respondents, divided into three respondent types based on EV consideration and purchase behavior. The dataset contains respondent demographics, their purchased vehicle, up to five considered alternatives, feature-importance rankings, attitudes toward EVs, and social-network-related information. In this study, we specifically use respondents' reported social networks, including up to ten individuals in each network, whether those individuals know one another, and the vehicle models they own, to characterize potential interpersonal influence. The vehicle attribute dataset, compiled through prior research [4], contains 1,891 vehicle models and their associated attributes, such as price, powertrain, fuel economy, driving range, market segment, and brand. Together, these tabular datasets provide the behavioral and product-attribute information needed to analyze customer preferences, consideration and purchase outcomes, and market structure.

3.2 Step 2 - Data preprocessing and integration

The customer survey and vehicle attribute datasets were preprocessed and integrated to match customer-reported vehicles with standardized vehicle records. The original survey sample included 2,283 respondents, categorized into three groups based on their self-reported survey responses: 765 *non-EV buyers*, 755 *non-EV buyers who considered EVs*, and 763 *EV buyers*. In the survey data, non-analytic fields, including timestamps, response identifiers, and administrative metadata, were removed. Free-text vehicle responses, such as "Other" entries and misspellings, were manually corrected, and standardized vehicle identifiers were constructed from the year, make, and model fields for purchased, considered, and social-network vehicles. These standardized identifiers were used to align customer-reported vehicle records with the vehicle attribute table, allowing vehicle-level information such as vehicle type, segmentation, fuel economy, horsepower, engine size, estimated battery range, fuel tank capacity, and price to be appended where corresponding records were available.

After integration, additional vehicle-type filtering and consistency checks were applied. Hydrogen/fuel-cell and plug-in vehicles were excluded because their counts were too small to support meaningful comparison and to maintain consistency with the EV-versus-traditional focus of the analysis. The remaining vehicles were classified into two powertrain categories: traditional and electric vehicles. During the cleaning process, 124 consideration entries were removed because they duplicated the purchased vehicle, and 55 entries were removed because the reported year–make–model combinations were invalid or inconsistent with actual production records. These exclusions reduced the intermediate sample to 2,179 respondents.

A second screening step was then applied to ensure consistency between each respondent's survey-based EV outcome label and the observed vehicle records. Respondents were excluded when their recorded purchased or considered vehicles contradicted their self-reported group. For example, respondents who reported themselves as *EV buyers* were removed if their purchased vehicle was coded as a traditional vehicle. After this consistency screening, 1,469 respondents remained for network modeling: 756 *non-EV buyers*, 257 *non-EV buyers who considered EVs*, and 456 *EV buyers*. Because each network representation required different observed vehicle relationships, the final analytic sample varied by network type. The unidimensional network required both a purchased vehicle and at least one considered vehicle, whereas the bipartite network required only a purchased vehicle. The multidimensional network was constructed from purchased vehicles only, as it captures ownership and social-network structure rather than consideration-stage alternatives. Respondents were not excluded for lacking social-network contacts, but contacts without an associated vehicle were omitted. After these representation-specific filters were applied, the cleaned analytic table was converted into node and edge lists for each network representation. These node and edge lists defined the final network datasets used in the subsequent analyses.

3.3 Step 3 - Exploratory visualization and statistical association analysis

Figure 4 presents a mixed-measure heatmap summarizing correlations among vehicle attributes and customer variables. This analysis establishes an attribute-level baseline before constructing the network representations. In this analysis, *vehicle type* denotes the powertrain category (traditional or EV), while *segmentation* denotes body or market class (e.g., SUV, sedan, hatchback). The heatmap highlights strong associations among physically related vehicle variables and EV-related classification variables. For example, price is strongly correlated with horsepower ($r = 0.96$) and moderately correlated with engine displacement ($r = 0.62$), while fuel economy is strongly associated with vehicle type ($\eta = 0.98$), customer group ($\eta = 0.98$), and fuel type ($\eta = 0.98$). Because several variables are closely related by construction, especially vehicle type, fuel type, fuel economy, and the EV-based customer-group definition, the strongest associations are interpreted as descriptive evidence of attribute-level separation rather than as independent causal effects.

The more relevant pattern for this study is that EV consideration and purchase outcomes are more strongly differentiated by powertrain-related and performance-related vehicle attributes than by baseline demographic variables. The customer-group variable shows stronger associations with fuel economy ($\eta = 0.98$), fuel type ($V = 0.71$), horsepower ($\eta = 0.72$), and price ($\eta = 0.71$) than with demographic variables such as age ($V = 0.34$), gender ($V = 0.19$), education ($V = 0.21$), marital status ($V = 0.22$), and income ($V = 0.26$). Occupation shows a moderate association with customer group ($V = 0.46$), but the overall pattern remains that technical vehicle attributes are more strongly associated with EV consideration and purchase outcomes than baseline demographics. To assess the stability of these selected associations, bootstrap confidence intervals and permutation tests were computed for the vehicle-attribute, EV-classification, customer-group, brand, and demographic relationships discussed above. The tested relationships had permutation-test p-values below 0.001 after false-discovery-rate adjustment, and the bootstrap 95% confidence intervals supported the same overall interpretation [33, 34]. Certain estimated-battery-range cells are left blank because battery range is only observed for EV models, while engine displacement and fuel tank capacity are not meaningfully defined for those EV observations. These attribute-level patterns motivate the subsequent network analysis, which examines whether differences across buyer groups are also reflected in relational structures of consideration, purchase, and socially embedded ownership.

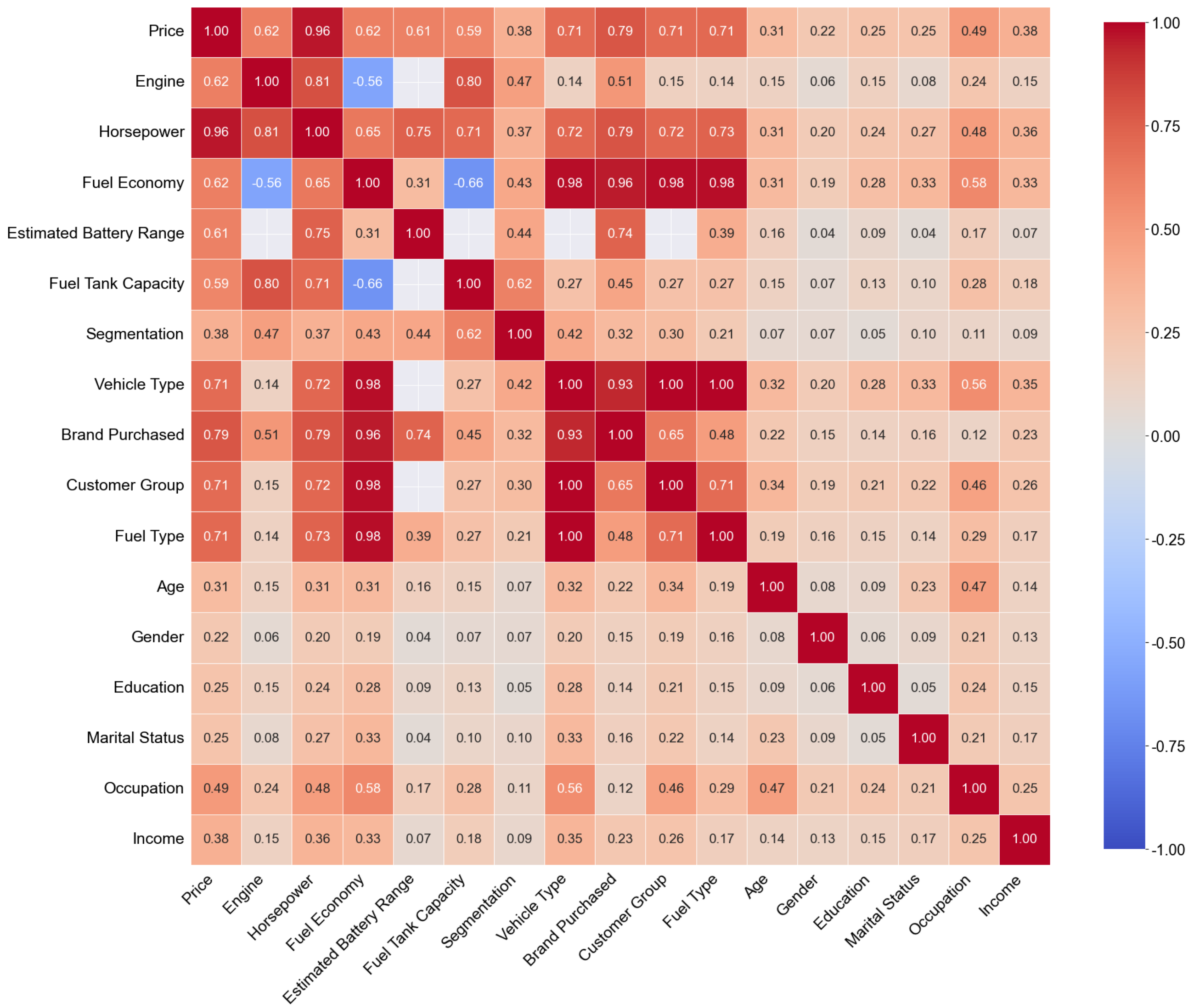

FIGURE 4: Correlation heatmap of vehicle attributes and customer demographics.

3.4 Step 4 - Network construction

In this section, the integrated customer–vehicle dataset is transformed into network representations to capture relational patterns in vehicle consideration and purchase behavior. Each representation was constructed from corresponding node and edge lists. In the unidimensional network, vehicle nodes were connected through purchased–considered and considered–considered vehicle pairs. In the bipartite network, customer nodes were connected to purchased and considered vehicle nodes. In the multidimensional network, customers, social-network contacts, and purchased-vehicle nodes were connected through ownership links and reported person–person social ties. Although constructed separately, these representations are analytical projections of the same underlying customer–vehicle–social relational data. Separating them helps isolate what is gained or lost when moving from product-level competition, to customer–vehicle decision sets, to socially embedded ownership structure. The resulting node and edge lists were used for network-metric computation and were exported to Gephi for visualization using a Fruchterman–Reingold force-directed layout.

We first visualize the full sample under the unidimensional, bipartite, and multidimensional representations shown in the bottom row of Figure 3. These full-sample visualizations highlight how different network dimensions preserve different aspects of the same customer–vehicle system. We then illustrate variation across customer segments using the multidimensional representation. The rightmost column of Figure 3 shows the corresponding networks for non-EV buyers, non-EV buyers who considered EVs, and EV buyers.

3.4.1 Network visualization across different network dimensions

The unidimensional, bipartite, and multidimensional network representations are respectively given in Figure 5, 6, and 7. Figure 5 shows the overall unweighted unidimensional co-consideration network. This representation aggregates customer decisions into product–product relationships, emphasizing competitive overlap among vehicles. The network displays a clear core–periphery structure where many vehicles occupy a shared comparison space, while others reside in smaller, niche clusters. Although EVs comprise a clear minority of the vehicle nodes (9.75% EV vs. 90.25% traditional), their deep embedding within the network suggests they regularly enter mainstream cross-shopping consideration sets. In this unweighted representation, a node's degree denotes its breadth of competition, measured by the number of unique alternatives co-considered by customers. Notably, the 2022 Tesla Model X exhibits the highest connectivity (84 links), therefore, functioning as a central anchor that spans a wide variety of alternatives and links EV choices to many traditional competitors.

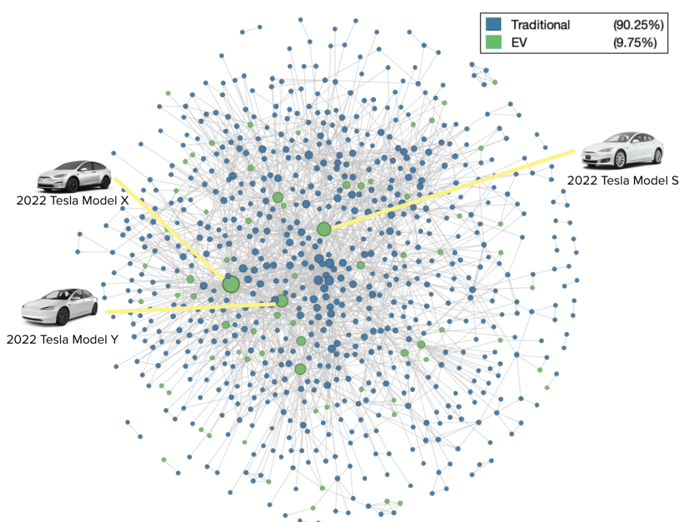

FIGURE 5: Unidimensional co-consideration network of all customer groups (# of nodes: 769, # of links: 2322).

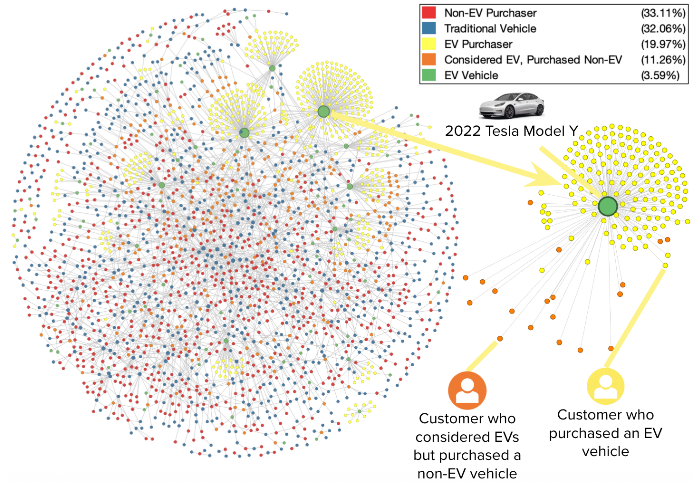

FIGURE 6: Overall bipartite network linking customers to vehicles included in their observed decision sets (purchased and considered). Customers are colored by segment and vehicles by powertrain type; the ego neighborhood of the highest-degree vehicle (2022 Tesla Model Y; degree = 170) is highlighted.

Figure 6 shows the overall bipartite network, in which customers and vehicles form two distinct node sets and edges record observed customer–vehicle relationships. Unlike the unidimensional projection, this representation preserves which customers are linked to which vehicles, including both purchased and considered vehicles. As a result, it reveals heterogeneity in observed decision-set size and makes it possible to distinguish vehicles that repeatedly appear across many customers' decision sets. The prominence of the Tesla Model Y in this graph illustrates that some EV models attract attention from multiple buyer types. More importantly, the bipartite representation shows that the same vehicle can play different roles across customers, serving as a purchased vehicle for some and a considered alternative for others. Thus, relative to the unidimensional network, the bipartite form shifts the analysis from product-level competition to customer-level attachment to alternatives.

Figure 7 presents the overall multidimensional network, which integrates customers, their social-network contacts, purchased vehicles, and vehicles owned by those contacts. In contrast to the first two representations, this network does not model consideration-stage alternatives; instead, it preserves ownership embedded in the social context. The resulting structure is denser and more layered because it combines purchase ties with interpersonal relationships. In this setting, vehicle centrality no longer indicates co-consideration breadth or customer attention alone, but rather how strongly a vehicle is embedded within the broader ownership and social system. The prominence of Tesla vehicles (2022 Tesla Model Y with 158 links is the vehicle node with the highest degree, followed by the 2022 Tesla Model X with 96 and the 2021 Tesla Model Y with 53) in this network indicates that some EVs are not only salient in decision sets but also central within socially embedded ownership patterns. Betweenness centrality provides a complementary view by identifying nodes that bridge less-connected parts of the network. The

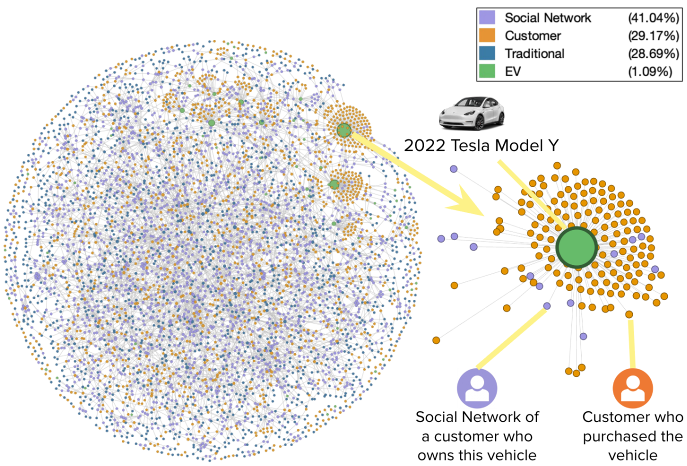

FIGURE 7: Overall multidimensional network integrating customers, social-network contacts, and purchased vehicle nodes. Node colors distinguish customers, social-network contacts, traditional vehicles, and EV models. The ego neighborhood of the highest-degree vehicle (2022 Tesla Model Y, degree = 158) is highlighted.

Ford F150 illustrates this distinction: although Tesla models have the highest degree, the Ford F150 has the third-highest betweenness centrality (0.085), suggesting that traditional vehicles can still play important bridging roles in the broader ownership network.

Taken together, these three representations provide complementary views of the same market. The unidimensional network highlights product-level competitive overlap, the bipartite network preserves customer-level links to purchased and considered vehicles, and the multidimensional network reveals socially embedded ownership structure. Therefore, increasing network dimensionality does not simply add detail; it changes the substantive meaning of centrality and the type of market organization that becomes visible.

3.4.2 Network visualization across different customer segments

The multidimensional networks for non-EV buyers, non-EV buyers who considered EVs, and EV buyers are respectively presented in Figure 8, 9, and 10. Figure 8 shows the multidimensional network for the non-EV buyers segment. This network is composed primarily of non-EV customers, their social-network contacts, and purchased vehicles, and it exhibits a broad, relatively diffuse structure. Multiple small social clusters are distributed across the network, while the interior remains connected through repeated links among customers, their contacts, and commonly owned traditional vehicles. The most connected vehicle is the 2022 Ford F150 (degree = 17), followed by the 2022 Chevrolet Equinox (15) and 2022 Honda CRV

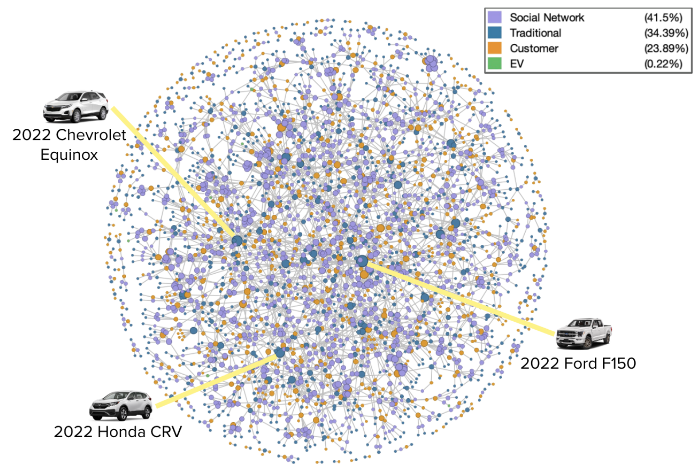

FIGURE 8: Multidimensional network for the non-EV buyers segment. Node colors distinguish customers, social-network contacts, traditional vehicles, and EV models. Labels highlight the vehicles with the highest degree in the segment.

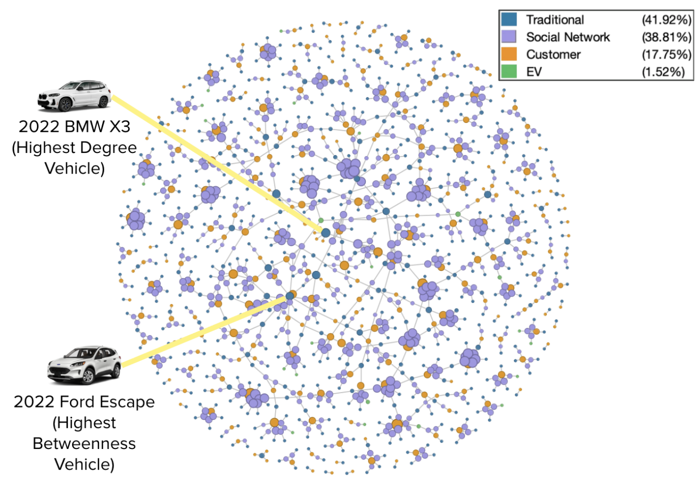

FIGURE 9: Multidimensional network for the non-EV buyers who considered EVs segment. Node colors distinguish customers, social-network contacts, traditional vehicles, and EV models. Labels indicate the vehicles with the highest degree and highest betweenness centrality in the segment.

(13). The same general pattern appears in betweenness centrality, where the 2022 Ford F150 also ranks first (0.0787), followed by the 2022 Chevrolet Equinox (0.0621) and 2022 Chevrolet Silverado 1500 (0.0550). This alignment indicates that mainstream traditional vehicles serve both as common ownership anchors and as bridges connecting otherwise separated customer and social-network neighborhoods.

Figure 9 presents the multidimensional network for non-EV

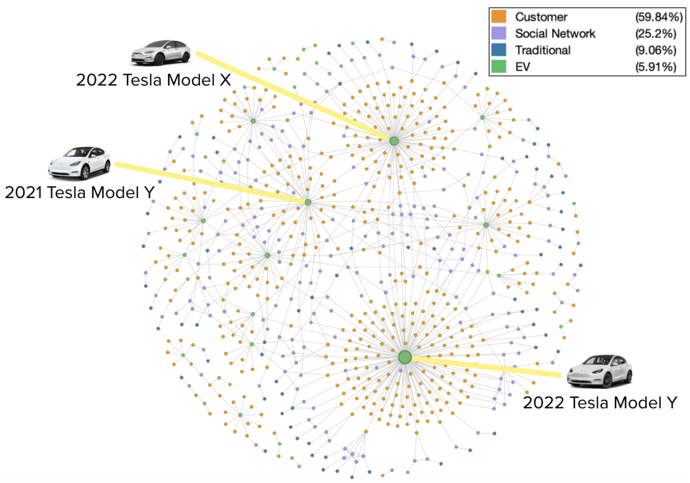

FIGURE 10: Multidimensional network for the EV buyers segment. Node colors distinguish customers, social-network contacts, traditional vehicles, and EV models. Labels highlight the dominant EV model hubs in the ownership-centered social network.

buyers who considered EVs. Compared with the non-EV buyers network, this graph is smaller and structurally more heterogeneous. Traditional vehicles still dominate, but EV nodes are present and dispersed throughout the network rather than isolated in a separate region. In this segment, the vehicles with the highest degree and highest betweenness are not the same. The 2021 BMW X3 has the highest degree (7), followed by the 2022 Ford F150 and 2021 Ford Bronco Sport (both 6). However, the 2022 Ford Escape has the highest betweenness (0.1359), followed by the 2022 Ford F150 (0.1255) and 2020 Chevrolet Equinox (0.1156). This indicates that the most frequently linked vehicles are not necessarily those that connect the network most strongly. In addition, in this segment, some traditional vehicles appear to function less as dominant hubs and more as structural bridges across customer and social-network neighborhoods. Relative to the non-EV buyers network, this distinction suggests a more differentiated and fragmented ownership structure, in which vehicle prominence depends not only on the number of direct ownership ties but also on a vehicle's position within the broader social structure.

Figure 10 shows the multidimensional network for EV buyers. In contrast to the other two segments, this network is highly concentrated around a small number of dominant EV hubs. The 2022 Tesla Model Y is the most central vehicle, with degree 157 and betweenness 0.4625, followed by the 2022 Tesla Model X (92, 0.2922) and the 2021 Tesla Model Y (51, 0.2055). Several star-like local structures are organized around these Tesla models, indicating that many customers and their social-network contacts are linked through a narrow set of repeated EV ownership anchors. Unlike the other segments, the close alignment between degree and betweenness suggests that the same EV models dominate both direct ownership ties and the principal bridging positions in the network.

Comparing the three multidimensional networks reveals clear differences in ownership and social embedding across customer groups, thereby contributing to RQ1. The non-EV buyers network is broad, traditional, and relatively diffuse, with mainstream traditional vehicles serving as both hubs and bridges. The non-EV buyers who considered EVs network remains centered on traditional vehicles, but it is more fragmented and structurally differentiated, with EVs present in the ownership-centered structure without becoming the dominant anchors. In contrast, the EV buyers network is strongly centralized around a small set of Tesla models that organize much of the observed customer and social-network connectivity.

3.5 Step 5 - Network analysis and comparison across network dimensions and customer segments

Table 1 summarizes the structural properties of the networks across dimensions and customer segments. As a sensitivity check, random perturbation tests were conducted by removing 5%, 10%, and 20% of nodes and edges over 100 repeated trials and recomputing the key network metrics. Retention was measured as the percentage of trials in which the original segment-level ordering or interpretation remained unchanged. The lowest observed retention rate across the primary findings was 87%, with most tested patterns retained in nearly all trials. These results suggest that the main segment-level patterns are not driven solely by a small number of individual nodes or reported ties.

In the unidimensional case, the overall network is large (769 nodes and 2,322 links) and highly connected, with 95.45% of nodes in the giant component, indicating substantial overlap in mainstream comparison sets. Segment-level patterns differ notably. The non-EV buyers network contains 501 nodes and 1,150 links, but only 85.23% of nodes are in the giant component, and its average path length within that component is the largest (4.57), suggesting a comparatively fragmented structure. The non-EV buyers who considered EVs network is similar in size (459 nodes and 1,115 links) but has a larger giant component (93.90%) and a higher clustering coefficient (0.72), indicating more tightly interconnected local neighborhoods of co-considered vehicles. The EV buyers network is much smaller (45 nodes and 89 links) and fully connected, with the shortest average path length (3.33). Its higher density (0.090) should be interpreted in light of its much smaller node set, since density is sensitive to network size.

In the bipartite networks, customers and vehicles form distinct node sets, and an edge indicates that a customer included a vehicle in the observed decision set, either as purchased or considered. Under this definition, average customer degree repre-

TABLE 1: Summary of network measurement results.

Representations	Metric	Overall	Non-EV buyers	Non-EV buyers, considered EV	EV buyers
Unidimensional	Avg. Degree	6.04	4.59	4.86	3.96
	Avg. Clustering Coefficient	0.56	0.52	0.72	0.65
	Network Density	0.0079	0.0092	0.011	0.090
	Giant Component %	95.45	85.23	93.90	100
	Avg. Path Length (GC)	3.93	4.57	3.93	3.33
Bipartite	Avg. Degree (vehicles per customer, i.e., decision-set size)	2.01	2.05	3.35	1.17
	Avg. Degree (customers per vehicle, i.e., # of customer reach)	3.62	2.80	1.88	8.9
	Network Density	0.0025	0.0037	0.0073	0.020
Multidimensional	Avg. Degree (customers)	2.41	2.74	3.19	1.42
	Avg. Degree (social-network contacts)	3.82	3.89	4.12	2.45
	Avg. Degree (purchased vehicles)	2.36	1.89	1.30	5.69
	Avg. Clustering Coefficient (social network)	0.53	0.59	0.67	0.14
	Network Density	0.00059	0.00092	0.0019	0.0030
	Giant Component (%)	93.15	88.75	63.60	90.16

sents the average observed decision-set size. The non-EV buyers who considered EVs segment has the largest decision sets on average (3.35 vehicles per customer), compared with non-EV buyers (2.05) and EV buyers (1.17). This indicates that the intermediate segment has the broadest set of linked alternatives in the bipartite representation. The vehicle-side average degree, reported as average customer reach, shows the opposite pattern. Vehicles in the EV buyers network have the highest average reach (8.9 customers per vehicle), compared with 2.80 for non-EV buyers and 1.88 for the intermediate segment. Thus, although EV buyers are linked to fewer vehicles on average, those vehicles are shared across more customers, indicating a more concentrated vehicle space. Consistent with this pattern, the EV buyers bipartite network also has the highest density (0.020), though this measure should be interpreted cautiously because it depends on the relative sizes of the two partitions.

The multidimensional networks reveal additional differences in scale and organization. The non-EV buyers segment is the largest across all three node categories, with 756 customers, 1,313 social-network nodes, and 1,095 purchased-vehicle nodes. The EV buyers segment also includes many customers (456), but far fewer purchased-vehicle nodes (114) and social-network nodes (192), indicating concentration around a narrower set of vehicles. The non-EV buyers who considered EVs segment is intermediate in size, but its structural properties are distinct. Most notably, the non-EV buyers who considered EVs segment combines the highest average degree for customers (3.19) and social-network nodes (4.12), and the highest social-subnetwork clustering coefficient (0.67). These values indicate the strongest local social cohesion among the three segments. At the same time, this segment has the lowest giant-component share (63.60%), implying that the overall network is more fragmented into relatively tight local groups rather than a single dominant connected structure.

The other two segments depart from this pattern in different ways. The non-EV buyers network has a larger giant component (88.75%) and moderately high social-subnetwork clustering (0.59), suggesting a broad shared core linking the traditional ownership and social structure. The EV buyers network also has a high giant-component share (90.16%), but it has by far the lowest social-subnetwork clustering coefficient (0.14) and the fewest social-network contacts per customer (0.42). This suggests that the EV buyers network is globally connected but socially less clustered, with cohesion arising more from repeated attachment to shared vehicle hubs than from dense social triangles. This interpretation is supported by the average degree of purchased-vehicle nodes, which is much higher for EV buyers (5.69) than for non-EV buyers (1.89) or non-EV buyers who considered EVs (1.30). Likewise, 7.29% of buyer-social contact ties in the EV buyers segment share the same purchased vehicle, compared with 1.45% for non-EV buyers and 1.07% for the intermediate segment. Together, these patterns indicate that EV buyers exhibit a narrower but more ownership-concentrated form of social overlap.

3.6 Step 6 - Interpretation and study outputs

The combined results suggest that EV consideration and purchase patterns are not simply a matter of replacing a traditional vehicle with an EV. Instead, the three buyer groups differ in how broadly they compare vehicles, which vehicles anchor their decision sets, and how purchased vehicles are embedded within the reported social-network structure. Section 3.3 shows that EV consideration and purchase outcomes are more strongly associated with powertrain-related attributes, especially fuel economy, vehicle type, and fuel type, than with demographic variables. The network results refine this interpretation. In the unidimensional representation, the *non-EV buyers who considered EVs* segment shows the strongest cross-type mixing and the highest local clustering, indicating that EV consideration broadens and restructures the competitive field even when an EV is not ultimately purchased. In the bipartite representation, the same segment exhibits the broadest observed decision sets, confirming that these customers attach to the widest range of alternatives. In the multidimensional representation, however, this intermediate group becomes the most socially cohesive at the local level while also being the most fragmented globally, suggesting that EV consideration without purchase is associated with many tight but relatively separate local ownership and social neighborhoods rather than one unified market structure. Taken together, these patterns indicate that the intermediate segment is not simply a group of EV considerers who ultimately purchased non-EVs. Within the observed market structure, this segment is the most heterogeneous: EVs enter its consideration sets and network neighborhoods, but traditional vehicles remain the primary anchors of final purchase and ownership structure. In this sense, the segment occupies a structurally intermediate position between non-EV-only buyers and EV buyers, reflecting EV engagement that has not translated into EV purchase within the observed dataset.

A second major interpretation is that network dimensionality reveals different forms of centrality and, therefore, different aspects of market organization. In the unidimensional co-consideration networks, EV models, especially Tesla vehicles, are highly central despite representing a minority of vehicle nodes, indicating that they serve as comparison anchors within the broader competitive field rather than simply reflecting market share. In the bipartite networks, this prominence is clarified from the customer side: EV-engaged segments show that a relatively small set of EV models occupies structurally important positions in observed decision sets, highlighting repeated customer attachment rather than only product–product overlap. The multidimensional analysis adds a different interpretation by embedding purchased vehicles within the customer and social-network structure. At the full-market level, EV models represent a small share of vehicle nodes, but some occupy disproportionately central positions in socially embedded ownership patterns. This pattern is strongest in the EV buyers segment, where the network is organized around a small number of dominant Tesla hubs that rank highly in both degree and betweenness. The EV buyers segment also shows much higher purchased-vehicle-node degree and buyer-social-contact same-vehicle overlap than the other groups, indicating that EV buyers are linked to fewer but more widely shared vehicles and are more likely to be socially connected to others who own the same model. By contrast, the non-EV buyers and non-EV buyers who considered EVs networks remain anchored primarily by traditional vehicles. In the intermediate segment, the mismatch between the highest-degree and highest-betweenness vehicles further shows that the vehicle most frequently linked is not necessarily the most important structural bridge. Taken together, these results show that vehicle prominence depends on representation: a vehicle may be central as a comparison anchor in co-consideration space, a repeatedly shared option in customer decision sets, or a hub or bridge in a socially embedded ownership structure, and these roles are not equivalent.

4 DISCUSSION

The results provide two main implications for the research questions of this study. Regarding RQ1, the findings suggest that buyer groups with different EV consideration and purchase outcomes differ not only in the vehicles they select, but also in how those vehicles are positioned within consideration, purchase, and socially embedded ownership structures. Non-EV buyers remain anchored around traditional vehicles, non-EV buyers who considered EVs exhibit the most heterogeneous structure, and EV buyers concentrate around a smaller set of EV-centered hubs. Regarding RQ2, cross-dimensional comparison reveals that vehicle prominence depends heavily on the network representation. A vehicle may act as a co-consideration anchor in a unidimensional network, a frequently shared option in a bipartite network, or a structural bridge in a multidimensional social network. Thus, these representations yield complementary insights rather than interchangeable views.

These findings also offer practical value for market analysis and decision support. For manufacturers, co-consideration networks can identify benchmark vehicles and competitive neighborhoods, showing which models customers compare and where EVs enter the competitive set. The non-EV buyers who considered EVs segment is especially useful from this perspective because it highlights cases where EVs enter consideration but do not translate into EV purchase. This structure can help manufacturers identify product-positioning gaps, competitive alternatives, or customer segments where EV interest exists but final purchase remains anchored to traditional vehicles. For policymakers and infrastructure planners, these preference patterns should be interpreted alongside charging-access conditions, since product preference and network structure alone do not fully capture infrastructure-related barriers to EV purchase. For customers, market analysts, and decision makers, the framework compares vehicles by both attributes and their roles in broader decision and ownership networks.

Several limitations should be acknowledged when interpreting these results. First, the study is based on a cross-sectional survey collected during a single time period. As a result, the analysis captures customer preferences, EV consideration, and network structure as a static snapshot rather than as an evolving process. The framework therefore cannot directly examine how vehicle competition, customer segments, or social exposure change over time, nor can it determine whether observed network positions precede or follow purchase outcomes.

Second, part of the dataset is self-reported, including considered vehicles and social-network vehicle information. This introduces the possibility of recall error, incomplete reporting, and misclassification. Although substantial preprocessing, cleaning, and consistency screening were applied, the resulting networks still depend on respondents' ability to accurately report both their own decision sets and aspects of their social environment. This limitation is especially relevant for the multidimensional network, which reflects reported social context rather than directly observed interpersonal influence. Additionally, the reported social-network ties may omit strong or weak relationships that were not captured by the survey, meaning that the network should be interpreted as a reported social context rather than a complete map of interpersonal influence.

Third, the current analysis does not incorporate direct charging-infrastructure measures into the attribute or network models, such as public charger density, charger reliability, distance to charging stations, or regional charging access. This scope limitation is critical because charging access can influence both EV consideration and its translation into purchase. As a result, the findings should be interpreted as describing patterns in vehicle attributes, customer–vehicle relations, and reported social-network structure, rather than as a complete explanation of all factors shaping EV purchase behavior.

Finally, the preprocessing rules required for consistent network construction reduced the final sample and, in some cases, narrowed particular customer groups. The unidimensional, bipartite, and multidimensional networks also use different inclusion rules, resulting in non-identical analytic samples. In addition, the network analyses preserve vehicles at the standardized model level rather than aggregating nodes by make, model family, or market segment. This choice retains the specific alternatives reported in customer consideration and purchase decisions, but it does not directly examine how broader brand-level or segment-level groupings would change the observed network structure. Plug-in vehicles were also excluded to focus on EV versus traditional comparisons. While this improves interpretability for the present study, it omits an intermediate electrification category that may play an important role in real-world electrification pathways.

5 CONCLUSION

This research developed a data-driven framework for analyzing heterogeneous customer preferences in the U.S. vehicle market using unidimensional, bipartite, and multidimensional network representations. By integrating customer survey data, vehicle attribute data, and reported social-network information, the study examined how EV consideration and purchase behavior vary across customer groups and how different network representations reveal different aspects of market structure. The exploratory analysis showed that EV consideration and purchase outcomes are most strongly associated with powertrain-related vehicle attributes, while demographic effects are comparatively weaker at the aggregate level.

The case study further suggests that EV purchase behavior is associated with a structural reorganization of the observed customer–vehicle system rather than a simple one-to-one substitution from a traditional vehicle to an EV. For RQ1, holding network representation fixed, the three buyer groups are structurally distinct: *non-EV buyers* remain broader and more strongly anchored by traditional vehicles, *non-EV buyers who considered EVs* form the most structurally heterogeneous intermediate segment, and *EV buyers* are the most concentrated around a narrow EV-centered core. For RQ2, increasing network dimensionality does not simply add more detail to the same picture; instead, it changes the kind of information that becomes visible about the market system. The unidimensional representation highlights product-level competitive overlap, the bipartite representation preserves customer-level attachment to alternatives, and the multidimensional representation reveals how purchased vehicles are situated within a broader social environment. In this sense, the same market can appear competition-centered, customer-centered, or socially embedded depending on which relational structure is retained.

Methodologically, the main contribution of this study is the systematic comparison of multiple network dimensions within the same EV customer-preference setting using observed customer-centered social-network information. More broadly, the study advances a relational perspective on customer preference modeling by showing that product competition, customer heterogeneity, and social embedding can be analyzed within a common framework. Future work can extend this framework in several directions. One direction is to connect the descriptive network patterns identified here to explanatory and predictive modeling by combining network-derived features with customer and vehicle attributes to estimate conditions associated with EV consideration, purchase, or non-purchase outcomes. A second direction is to conduct more formal local-structure analysis, such as network motif or recurring-neighborhood analysis, to identify the dominant small-scale building blocks in each representation. A third direction is to expand the framework to include additional powertrain categories, especially plug-in hybrids, and to apply the same multi-representation approach to other product markets in order to distinguish vehicle-market-specific findings from more general principles of socially embedded customer choice.

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REFERENCES

[1] International Energy Agency, 2025. Global ev outlook 2025: Expanding sales in diverse markets. Tech. rep., IEA.

[2] Putzig, M., Bennett, J., Brown, A., Lommele, S., and Bopp, K., 2021. Electric vehicle basics. Tech. rep., National Renewable Energy Lab.(NREL), Golden, CO (United States).

[3] Sha, Z., Cui, Y., Xiao, Y., Stathopoulos, A., Contractor, N., Fu, Y., and Chen, W., 2023. "A network-based discrete choice model for decision-based design". *Design Science,* ***9***, p. e7.

[4] Gavino, P. A., Xiao, Y., Cui, Y., Chen, W., and Sha, Z., 2023. "Evolutionary co-mention network analysis via social media mining". In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Vol. 87301, American Society of Mechanical Engineers, p. V03AT03A045.

[5] Xiao, Y., Cui, Y., Koskinen, J., Contractor, N., Chen, W., and Sha, Z., 2025. "Product design incorporating competition relations: A network-based design framework considering local dependencies". *Journal of Mechanical Design,* ***147***(2), p. 021702.

[6] Cui, Y., Sun, Z., Xiao, Y., Sha, Z., Koskinen, J., Contractor, N., and Chen, W., 2025. "Network analysis of two-stage customer decisions with preference-guided market segmentation". *Journal of Computing and Information Science in Engineering,* ***25***(6), p. 061003.

[7] Egbue, O., and Long, S., 2012. "Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions". *Energy policy,* ***48***, pp. 717–729.

[8] Ajzen, I., 1991. "The theory of planned behavior". *Organizational behavior and human decision processes,* ***50***(2), pp. 179–211.

[9] Jansson, J., Marell, A., and Nordlund, A., 2011. "Exploring consumer adoption of a high involvement eco-innovation using value-belief-norm theory". *Journal of Consumer Behaviour,* ***10***(1), pp. 51–60.

[10] Schuitema, G., Anable, J., Skippon, S., and Kinnear, N., 2013. "The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles". *Transportation Research Part A: Policy and Practice,* ***48***, pp. 39–49.

[11] Wang, S., Fan, J., Zhao, D., Yang, S., and Fu, Y., 2016. "Predicting consumers' intention to adopt hybrid electric vehicles: using an extended version of the theory of planned behavior model". *Transportation,* ***43***(1), pp. 123–143.

[12] Axsen, J., and Kurani, K. S., 2012. "Social influence, consumer behavior, and low-carbon energy transitions". *Annual Review of Environment and Resources,* ***37***(1), pp. 311–340.

[13] Krupa, J. S., Rizzo, D. M., Eppstein, M. J., Lanute, D. B., Gaalema, D. E., Lakkaraju, K., and Warrender, C. E., 2014. "Analysis of a consumer survey on plug-in hybrid electric vehicles". *Transportation Research Part A: Policy and Practice,* ***64***, pp. 14–31.

[14] Peters, A., and Dütschke, E., 2014. "How do consumers perceive electric vehicles? a comparison of german consumer groups". *Journal of Environmental Policy & Planning,* ***16***(3), pp. 359–377.

[15] Carley, S., Krause, R. M., Lane, B. W., and Graham, J. D., 2013. "Intent to purchase a plug-in electric vehicle: A survey of early impressions in large us cites". *Transportation Research Part D: Transport and Environment,* ***18***, pp. 39–45.

[16] Barbarossa, C., Beckmann, S. C., De Pelsmacker, P., Moons, I., and Gwozdz, W., 2015. "A self-identity based model of electric car adoption intention: A cross-cultural comparative study". *Journal of Environmental Psychology,* ***42***, pp. 149–160.

[17] Stern, P. C., 2000. "New environmental theories: toward a coherent theory of environmentally significant behavior". *Journal of social issues,* ***56***(3), pp. 407–424.

[18] Graham-Rowe, E., Gardner, B., Abraham, C., Skippon, S., Dittmar, H., Hutchins, R., and Stannard, J., 2012. "Mainstream consumers driving plug-in battery-electric and plug-in hybrid electric cars: A qualitative analysis of responses and evaluations". *Transportation Research Part A: Policy and Practice,* ***46***(1), pp. 140–153.

[19] Gadenne, D., Sharma, B., Kerr, D., and Smith, T., 2011. "The influence of consumers' environmental beliefs and attitudes on energy saving behaviours". *Energy policy,* ***39***(12), pp. 7684–7694.

[20] Bonges III, H. A., and Lusk, A. C., 2016. "Addressing electric vehicle (ev) sales and range anxiety through parking layout, policy and regulation". *Transportation Research Part A: Policy and Practice,* ***83***, pp. 63–73.

[21] Hackbarth, A., and Madlener, R., 2013. "Consumer preferences for alternative fuel vehicles: A discrete choice analysis". *Transportation Research Part D: Transport and Environment,* ***25***, pp. 5–17.

[22] Axsen, J., Orlebar, C., and Skippon, S., 2013. "Social influence and consumer preference formation for pro-environmental technology: The case of a uk workplace electric-vehicle study". *Ecological Economics,* ***95***, pp. 96–107.

[23] Wang, M., Chen, W., Huang, Y., Contractor, N. S., and Fu, Y., 2016. "Modeling customer preferences using multidimensional network analysis in engineering design". *Design Science,* ***2***, p. e11.

[24] Cui, Y., Ahmed, F., Sha, Z., Wang, L., Fu, Y., Contractor, N., and Chen, W., 2022. "A weighted statistical network modeling approach to product competition analysis". *Complexity,* ***2022***(1), p. 9417869.
[25] Wang, M., Chen, W., Huang, Y., Contractor, N. S., and Fu, Y., 2015. "A multidimensional network approach for modeling customer-product relations in engineering design". In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Vol. 57175, American Society of Mechanical Engineers, p. V007T06A044.
[26] Swinscow, T. D. V., Campbell, M. J., et al., 2002. *Statistics at square one*. No. Ed. 10. Bmj London.
[27] Cramér, H., 1999. *Mathematical methods of statistics*, Vol. 9. Princeton university press.
[28] Fisher, R. A., 1970. "Statistical methods for research workers". In *Breakthroughs in statistics: Methodology and distribution*. Springer, pp. 66–70.
[29] Sha, Z., Huang, Y., Fu, J. S., Wang, M., Fu, Y., Contractor, N., and Chen, W., 2018. "A network-based approach to modeling and predicting product coconsideration relations". *Complexity,* ***2018***(1), p. 2753638.
[30] Wang, M., Sha, Z., Huang, Y., Contractor, N., Fu, Y., and Chen, W., 2018. "Predicting product co-consideration and market competitions for technology-driven product design: a network-based approach". *Design Science,* ***4***, p. e9.
[31] Wang, M., and Chen, W., 2015. "A data-driven network analysis approach to predicting customer choice sets for choice modeling in engineering design". *Journal of Mechanical Design,* ***137***(7), p. 071410.
[32] Fu, J. S., Sha, Z., Huang, Y., Wang, M., Fu, Y., and Chen, W., 2017. "Two-stage modeling of customer choice preferences in engineering design using bipartite network analysis". In International design engineering technical conferences and computers and information in engineering conference, Vol. 58127, American Society of Mechanical Engineers, p. V02AT03A039.
[33] Good, P., 2005. *Permutation, parametric and bootstrap tests of hypotheses*. Springer.
[34] Benjamini, Y., and Hochberg, Y., 1995. "Controlling the false discovery rate: A practical and powerful approach to multiple testing". *Journal of the Royal Statistical Society: Series B (Methodological),* ***57***(1), pp. 289–300.

A Appendix A: Mathematical equations for correlation calculation

For continuous–continuous pairs (e.g., vehicle price, power, fuel economy), we use Pearson's correlation coefficient,

$$r_{XY} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}}, \tag{A1}$$

where x_i and y_i are the ith paired observations of variables X and Y, $\bar{x}$ and $\bar{y}$ are sample means, and n is the number of non-missing paired observations used for that specific variable pair [26]. Pearson coefficients range from -1 to $+1$ and retain directionality.

For categorical–categorical pairs (e.g., product class, market segment, customer-group outcomes, and demographic categories), we use Cramér's V based on the contingency-table chi-squared statistic,

$$V = \sqrt{\frac{\chi^2}{n\min(r-1,c-1)}}, \tag{A2}$$

where χ^2 is Pearson's chi-squared statistic computed from the $r \times c$ contingency table, r and c are the number of row and column categories, and n is the total number of observations contributing to the table [27]. Cramér's $V \in [0,1]$ measures association strength without sign.

For categorical–continuous pairs (e.g., how product class or segmentation relates to price or fuel economy), we use the correlation ratio (η), which compares between-group variation to total variation,

$$\eta^2 = \frac{\sum_{k=1}^{K} n_k(\bar{y}_k-\bar{y})^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}, \qquad \eta = \sqrt{\eta^2}, \tag{A3}$$

where Y is the continuous variable, G is a categorical grouping variable with K levels, n_k is the number of observations in group k, $\bar{y}_k$ is the group mean, $\bar{y}$ is the overall mean, and n is the total number of observations [28]. The statistic $\eta \in [0,1]$ quantifies the strength of association (no directionality).

B Appendix B: Summary of network measurements used in this work

TABLE B1: Summary of network metrics used for market analysis.

Network metric and short definition	**Equation**	**Interpretation in market analysis**
Number of Nodes and Links Number of entities and relationships in the network.	$\lvert V\rvert =$ number of nodes, $\qquad \lvert E\rvert =$ number of links where V is the set of nodes and E is the set of links.	These metrics describe the scale of a networked market system. In a vehicle-market context, for example, a larger number of vehicle nodes would indicate a broader product space, while a larger number of links would indicate more observed competition, overlap, or interaction among entities. Comparing node and link counts across groups helps reveal whether one market segment is broader, more concentrated, or more fragmented than another.
Degree / Average degree Degree is the number of direct links of a node. Average degree summarizes connectivity across all nodes.	$k_i = \sum_j a_{ij}$ $\bar{k} = \frac{1}{\lvert V\rvert} \sum_{i \in V} k_i$ For a simple undirected one-mode graph, $\bar{k} = \frac{2\lvert E\rvert}{\lvert V\rvert}$ where k_i is the degree of node i, $a_{ij} = 1$ if nodes i and j are connected and $a_{ij} = 0$ otherwise, $\lvert V\rvert$ is the number of nodes, and $\lvert E\rvert$ is the number of links.	Degree measures the breadth of direct competition or attachment. In a vehicle-market example, a vehicle with high degree would be linked to many alternatives or many customers and therefore occupy a broad market position. Average degree summarizes how connected the market is overall. Higher values indicate broader overlap among alternatives or stronger concentration of customer attention around particular products.
Density Fraction of possible links that are realized.	For a simple undirected network, $D = \frac{2\lvert E\rvert}{\lvert V\rvert(\lvert V\rvert - 1)}$ For a bipartite network with node sets U and W, $D_{\text{bip}} = \frac{\lvert E\rvert}{\lvert U\rvert\lvert W\rvert}$ where D is density, $\lvert E\rvert$ is the number of links, $\lvert V\rvert$ is the number of nodes, and $\lvert U\rvert$ and $\lvert W\rvert$ are the sizes of the two node partitions.	Density measures how saturated a network is with observed links. A high-density network indicates that many possible competitive or relational ties are realized, suggesting a tightly interconnected structure. A low-density network indicates a sparser structure with fewer overlaps and more selective comparison, interaction, or ownership patterns.
Clustering coefficient Tendency of a node's neighbors to also connect to each other.	For node i, $C_i = \frac{2e_i}{k_i(k_i - 1)}$ and the average clustering coefficient is $\bar{C} = \frac{1}{\lvert V\rvert} \sum_{i \in V} C_i$ where C_i is the clustering coefficient of node i, e_i is the number of realized links among the neighbors of node i, k_i is the degree of node i, and $\lvert V\rvert$ is the total number of nodes.	Clustering measures local cohesion. In a vehicle-market context, a vehicle with high clustering would lie in a tightly connected neighborhood where its competitors are also linked to one another. More generally, high clustering often reflects a cohesive market segment or localized comparison group, whereas low clustering suggests that a node connects across less tightly knit neighborhoods.

TABLE B2: Summary of network metrics used for market analysis (continued).

Network metric and short definition	**Equation**	**Interpretation in market analysis**
Giant component percentage $(GC\%)$ Share of nodes belonging to the largest connected component.	$$GC\% = \frac{\lvert V_{\mathrm{GC}} \rvert}{\lvert V \rvert} \times 100$$ where $\lvert V_{\mathrm{GC}} \rvert$ is the number of nodes in the largest connected component and $\lvert V \rvert$ is the total number of nodes in the network.	This metric measures whether the network is organized around one dominant connected structure or many smaller disconnected pieces. A high giant-component percentage indicates that most nodes belong to one main competitive or relational system. A lower value suggests fragmentation, meaning that multiple relatively separate market regions, customer neighborhoods, or product communities coexist.
Average path length Average shortest-path distance between node pairs.	$$L = \frac{1}{N(N-1)} \sum_{i \neq j} d(i,j)$$ where L is average path length, $d(i,j)$ is the shortest-path distance between nodes i and j, and N is the number of nodes in the connected component being analyzed.	Average path length measures how far apart nodes are in the network. A lower value means that products, customers, or social contacts can be connected through fewer intermediaries, indicating a more compact structure. A larger value suggests a more diffuse network. In market terms, shorter paths imply that entities are more closely tied within the overall competitive or relational system.
Betweenness centrality Number of times a node acts as a bridge along the shortest path between two other nodes.	$$BC(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$ where $BC(v)$ is the betweenness centrality of node v, σ_{st} is the number of shortest paths between nodes s and t, and $\sigma_{st}(v)$ is the number of those paths that pass through node v.	Betweenness captures brokerage or bridging importance. For example, a vehicle with high betweenness may not have the most direct links, but it may connect otherwise separate parts of the market. More generally, a high-betweenness node can link different customer neighborhoods, product groups, or social clusters that would otherwise be weakly connected.