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FORECASTING TECHNOLOGICAL IMPACTS ON CUSTOMERS' CO-CONSIDERATION BEHAVIORS: A DATA-DRIVEN NETWORK ANALYSIS APPROACH

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ABSTRACT

Forecasting customers' responses and market competitions is essential before launching major technological changes in product design. In this research, we present a data-driven network analysis approach to understand the interactions among technologies, products, and customers. Such an approach provides a quantitative assessment of the impact of technological changes on customers' co-consideration behaviors. The multiple regression quadratic assignment procedure (MRQAP) is employed to quantitatively predict product co-consideration relations as a function of various effect networks created by associations of product attributes and customer demographics. The uniqueness of the proposed approach is its capability of predicting complex relationships of product co-consideration as a network. Using vehicles as a case study, we forecast the impacts of two technological changes – adopting the fuel economy-boosting technology and the turbo engine technology by individual auto companies. The case study provides vehicle designers with insights into the change of market competitions brought by new technological developments. Our proposed approach links the market complexity to technology features and subsequently product design attributes to guide engineering design decisions in the complex customer-product systems.

1. INTRODUCTION

Advances in technology consistently stimulate the creation of new or improved products. Such a force that drives product innovation and moves industry forward is known as *technology push*. As Coombs et al. [2] argue, unlike market pull that often causes products to develop in an evolutionary way, technology push tends to cause revolutionary transformation. In automotive industry, for example, the improved electronics and software technology have enabled new telematics features for vehicles, such as automatic parallel parking, lane-keeping assistance, adaptive cruise control and blind spot detection. These semi-autonomous driver aids can significantly reduce the accidental risks while improving the driving experience.

Ideally new technologies would bring a profound effect on the market and shift customers' interests. However, the impact is not affirmative because high-tech features may not be well recognized and accepted by the public. This is due to the complex decision-making behaviors of individual customers and social interactions among customers. It is therefore of interest to understand if the adoption of new technologies would affect customers' consideration and buying decisions. In other words, the question is how to evaluate the market response triggered by new technologies, which, in turn, affect the final adoption of such new technologies in product design.

In this research, the complex relationship between customers and products is modeled as a socio-technical system. As shown in Fig. 1, customers' product consideration and choice behaviors are influenced by product design attributes, customer

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demographics, and customers' preferences. For example, the decision on vehicle purchase can be affected by the vehicle designs (such as color, engine size, roof widow, etc.), the customer demographics (such as income, social status, education background, etc.), and the personal tastes and desires. If a customer believes fuel economy being important, he/she is more likely to buy a vehicle model with small engine or hybrid power source. In order to influence customers' decisions to enhance products' market share, one way is to incorporate incentives or mechanisms to influence customer's decisions, while the other way is to modify the settings of product design attributes (e.g., by utilizing new technologies) based on the potential change to market, as illustrated in Fig. 1. In this paper, our focus is on the latter aspect. Different from existing works that survey customers' responses to new technology [1], we assess technological impact by evaluating the impact of the associated design attributes on customers' behaviors.

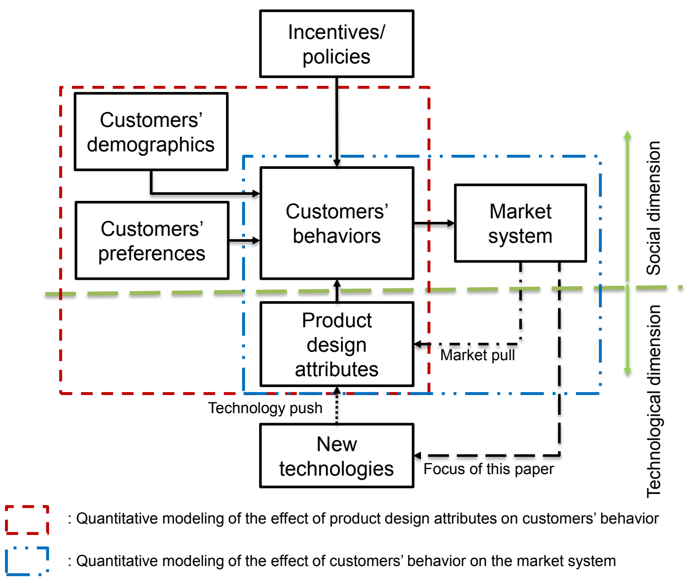


Figure 1. A social-technical system perspective on understanding and modeling interactions among technologies, products, customers and market.

Among different types of customers' behaviors, we are particularly interested in understanding customers' *co-consideration* decisions, and hence market competitions. Co-consideration describes the situation where multiple products are considered by a customer concurrently. Co-consideration involves the comparison and evaluation of similar products, and is a crucial step before customers make purchase decisions. A product would not be purchased if it is not in a customer's consideration set. Co-consideration also implies market competitions between set of products or brands, which is crucial for companies to plan for product positioning and marketing strategies. Existing studies [2-4] have shown that customers' consideration sets are small, often including two to six options due to the limited information processing ability of humans. As a result, subtle changes in consideration set (either size or elements) would directly affect the overall market competition. Understanding market competition poses new opportunities to better establish competitive design strategies, address customer needs and to make strategic enterprise moves (e.g., branding, positioning). However, the quantitative modeling framework, which enables the prediction of changes in co-consideration relations under different scenarios of technological applications, is not well established.

Our ***research objective*** in this paper is to develop an analytical approach to understand the connections between the underlying relations among product design attributes (engineering-driven product association) and customers' co-consideration (customer-driven product association). In this regard, we construct a network by modeling vehicles as nodes and the co-consideration relations as edges. The key idea is to model the market competitions as a product co-consideration network that can be predicted as a function of explanatory networks derived from the associations of product design and customer demographical attributes.

The remaining of the paper is structured as follows. In Section 2, we review existing studies on analyzing the technological impacts on product design and the studies on modeling customers' behaviors. To address the limitation of existing approaches identified in Section 2, we propose a data-driven network analysis based approach in Section 3. We also present a stepwise framework in this section to facilitate the implementation of such approach. In Section 4, the proposed approach is applied on China vehicle market data to understand customers' co-consideration behaviors of vehicles. The aim is to predict how the technologies changes, such as fuel economy boosting techniques and the turbocharged engine, would affect market competitions. In Section 5, the conclusion is made and closing thoughts are presented.

2. FRAME OF REFERENCES

Understanding the impact of new technologies and predicting the customer acceptance have drawn continuous interests since 1980s because of the growing technology developments (especially the information technology) and the increasing failure of technology adoption in organizations. The Technology Acceptance Model (TAM) proposed by Fred Davis [5] argues that the use of technology is a system response that can be explained and predicted by customers' motivation, which, in turn, is directly influenced by the systems' features. Such inner relationships are very similar to the interactions among product design attributes and customers' co-consideration behavior as shown in Fig. 1. Davis suggests that users' motivation can be explained by three factors: *Perceived Ease of Use*, *Perceived Usefulness* and *Attitudes Towards Using* the technology in which the first and the second factors are directly linked to the product design characteristics. Later development of TAM has evolved to many versions by substituting *Attitudes Towards Using* with *Behavioral Intention* [6]; adding extra variables as antecedents to *Perceived Usefulness* variable (called TAM2) [7]; and by identifying the antecedents to *Perceived Ease of Use* variable (called TAM3) [8]. Later research has also extended the TAM by including the social influence due to the increasing popularity of Internet and social media [9-11].

Although extensive studies exist in the field of diffusion of innovation, most of work are empirical and qualitative. They are hypothesis-based and focused more on using experimental data to test the hypothesized causal relationships. From the methodological perspective, the main limitation is the employment of self-reported use data (e.g., a subjective measurement of verbal description) for validation instead of the actual use data. The human subjects in survey may generate biased results that cannot be generalized to the real world [12].

In addition to the TAM theory, existing literature has used game theoretic models to quantitatively understand the impact of technology. Thatcher [13] developed a two-state duopoly competition model to examine the impact of information technology (IT) investments in product design tools on improving product quality and price, firm productivity and profits, and consumer welfare; He finds, however, these improvements are achieved with the compromise of productivity. Thatcher observes that profit-maximizing firms often leverage technology-based design tools to improve product quality, resulting in higher levels of firm profits and consumer welfare. Besides Thatcher's study, there are other similar theoretical studies, such as [14], but the analysis is performed in a monopolist context. In addition to the theoretical models, other studies have also been performed since early 1970s to investigate the impact of technology, especially in the field of IT on different levels of systems, including economic level, industrial level, firm level and application level. However, these studies do not analyze the impact at the individual customer level. Even if some of the existing studies [13, 15, 16] have realized the importance of taking customers into consideration, they focus more on providing economic insights, such as the impact on customers' welfare and surplus, rather than from the perspective of understanding the impact of engineering design.

The Discrete Choice Analysis (DCA) approach has been widely adopted as an analytical approach to understand customers' preferences in supporting engineering decisions [17, 18]. In essence, DCA is a utility-based approach, which uses utility to rank alternatives from a choice set. DCA provides predictions of purchase decisions given the choice set of each customer, however the method cannot capture the complex association relations of alternatives in co-considerations [19]. Even though academics and practitioners have begun to realize the importance of consideration behaviors in decision making [20-25], existing work in engineering design only explores the suitability of various forms of non-compensatory and compensatory models using synthetic data generated by pre-defined adjunctive rules [20]. However, the connections between the formation of consideration sets and the underlying driving factors associated with customer and product attributes may not always be clear.

As a summary, there are two major limitations of existing studies on analyzing and predicting technological impact and users' behaviors: 1) Limited usage of actual market data is found for quantitative data-driven modeling; 2) Few studies are seen in modelling customers' co-consideration behavior which involves the modeling of relations instead of utility ranks. Furthermore, the impact of product design and customer profiles on co-consideration decisions are not thoroughly understood. Without addressing these limitations, the question about how adopted technology may affect the customer decisions and the resulting market is still not well understood. Especially in a market involving multiple competitors, the lack of such understanding impedes enterprises to determine what design strategies should be applied in response to their competitors' strategies and whether specific design innovations are worthy of performing in order to gain more market competence. The answers are crucial to designers and also an enterprise to survive in today's market.

3. PROPOSED NETWORK ANALYSIS BASED APPROACH

3.1. Overview of the approach

In recent research, network analysis approach has been used to understand the complex relations between customers and products [19]. As opposed to other statistical approaches, a network analysis approach allows the study of patterns of relationships, representing the relationships graphically, and evaluating new relationships to develop the system further. In our prior research, product association networks are constructed based on co-consideration relations, and a heuristic algorithm was proposed to predict consumer choice sets when such information is missing in choice modeling [26]. Later, the unidimensional product association network is extended to a multidimensional customer-product network (MCPN) [19, 27] to model multiple types of relations, such as co-consideration and choice decisions, social interactions, and product dependencies. However, the network models developed in the past works are restricted to analyzing association structures and identifying critical factors that affect consumers' decisions. This paper is a first attempt to build a network model for the purpose of prediction. With a focus on the co-consideration relations of products, this work predicts the interdependency among products and the dynamic structural changes as impacts of technological changes.

As shown in Fig. 2, our proposed data-driven network analysis and prediction approach models a whole product market as a single network entity, where the dependency among product relations driven by customer preferences are analyzed. Central to the approach is a network analysis model which provides the statistical modeling of products' co-consideration network with respect to the changes of explanatory networks formed by the associations of product design attributes and customer demographic attributes. This is fundamentally different from the DCA approach that directly uses values of product attributes and consumer demographics as predictors. For example, the homophily effect [28] in the explanatory effect network represents the extent to which products form ties with similar versus dissimilar others. This effect can be tested in the developed network model in determining products' co-consideration relations. For predicting the technological impact, the network analysis model is used to predict product competitions or co-considerations under new technological scenarios. The network structural information in the predicted networks are then analyzed to generate the insights into market competition and product associations. In this work, market competition is viewed from both the perspective of a single product and the perspective of producers (i.e., a group of products within the same brand). From the next section onwards, we present each step of the proposed approach following the flow diagram in Fig. 2.

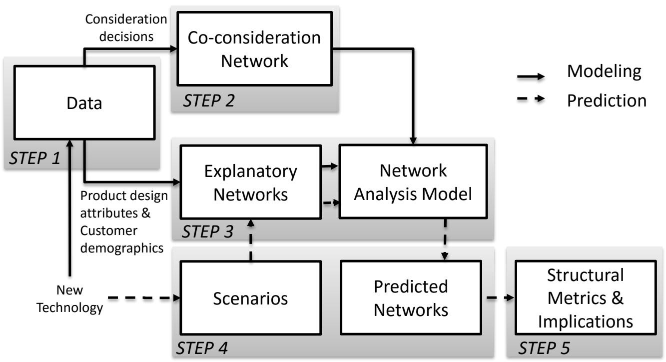


Figure 2. Overview of the proposed approach

3.2. Step 1 – Data collection

The first step involves data collection and preparation. The proposed approach requires data to cover at least two aspects: 1) the competing alternatives customers consider, and 2) the product attributes that customers consider, named as customer-desired product attributes (or product design attributes). For the former, stated choice experiments or revealed choice data can be used to identify consideration decisions made by individual customers. For the latter, either product survey or product specifications can be used for product description. In addition to the above categories, customer demographics and other preference-related information should also be collected to improve model performance.

3.3. Step 2 – Characterizing co-consideration preferences as an association network

The goal in step 2 is to construct a product association network for characterizing customers' co-consideration preferences. The customers' co-consideration decisions are represented by network edges (links) whereas product offerings are represented by network nodes. Based on the data collected in the previous step, the association ties between products can be built to reflect the proximity or similarity of two products in customers' considerations. For example, given that many customers consider "Ford Edge", "Ford Changan Kuga" and "Honda Dongfeng CR-V" together, we may extract the three vehicle models and establish edges between any pair of them (see Fig. 3). The strength of the edge can be evaluated by standard measures of association rules, showing how likely the two products are co-considered by a single customer. In Fig. 3, the strength between Edge and CR-V (1.2) is smaller than the strength between Kuga and CR-V (2.4), implying that after normalization, CR-V is more likely to be co-considered with Kuga than Edge by customers.

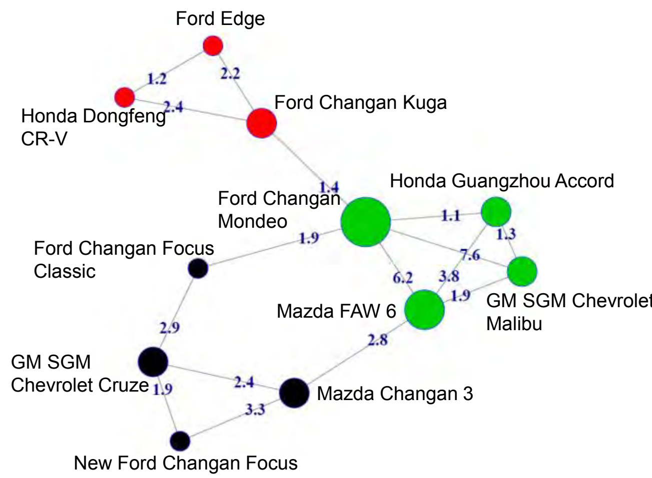


Figure 3: Illustrative network of vehicle associations

3.4. Step 3 – A network analysis model to predict co-consideration decisions

The goal of Step 3 is to build a quantitative network model based on the co-consideration network and the collected attribute data. In this work, the Multiple Regression Quadratic Assignment Procedure (MRQAP)[29] is employed. MRQAP model is selected due to its capability in predicting the product co-consideration relationship as a function of effect networks formed based on the associations of various of customer-desired product attributes and customer demographics [29].

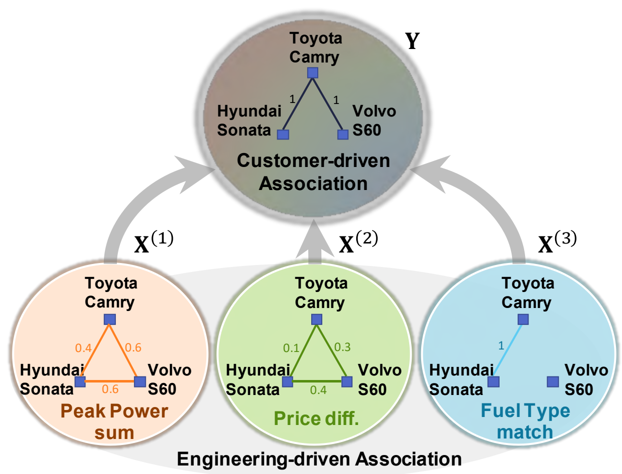


Figure 4: Illustration of MRQAP Model. Co-consideration decisions (Y at top) are predicted using product associations created by attribute data (Xs at bottom)

As illustrated in Fig. 4, the idea of the MRQAP approach is to decompose the complex customer-driven co-consideration relationships into a function of networks that represent engineering-driven associations of product attributes. The coefficients identified in a MRQAP model indicate the importance of individual effect networks in forming co-consideration relations. The response $\mathbf{Y}$ is the matrix formed by the binary edges representing the product co-consideration relations. At the bottom, the product attributes are vectorized as effect network $\mathbf{X}^{(k)}$, each measures the associations between pairs of products based on various arithmetic operations of attributes (peak power sum, price difference, and fuel type match are used as examples). The unique aspect of MRQAP is to use simple product networks $\mathbf{X}$ (created using attribute data) to *predict* the structure of the observed complex decision network $\mathbf{Y}$ (created using co-consideration data). Let Y_{ij} be the dependent co-consideration ties between vehicle i and j, and $X_{ij}^{(k)}$ be the k^{th} covariate (attribute) for the same edge observation. The MRQAP model is analogous to the standard logistic regression element-wise on network matrices, where the systematic component is given by:

$$Pr\ \left(Y_{ij}=1\right)=\mathrm{E}\left(Y_{ij}\right) = \frac{\exp\left(\beta_0+\beta_1 X_{ij}^{(1)}+\cdots+\beta_n X_{ij}^{(n)}\right)}{1+\exp\left(\beta_0+\beta_1 X_{ij}^{(1)}+\cdots+\beta_n X_{ij}^{(n)}\right)} \tag{1}$$

As shown in Table 1, the explanatory effect networks in our MRQAP model allow the modeling of two types of effects: the attribute-based main effect and the homophily effect. The attribute-based main effect tests whether products with a specific attribute (or with a high-valued attribute) is more likely to have consideration ties than products without the attribute (or with a low-valued attribute). An example is the peak power sum network. A positive parameter β associated with this network indicates that vehicles with higher sum of powers tend to be co-considered more than vehicles with lower sum of powers. Thus, a vehicle with a high peak power tends to express more co-consideration ties. The homophily effect, originated from social network literature, represents the tendency of entities to associate and bond with similar others. In the context of product association network, the homophily effect tests whether products with similar attributes tend to have ties with each other. One example is the price difference network. A negative parameter β suggests that vehicles with smaller difference in price are more likely to form co-consideration ties. In literature, it is often desirable to have both main effects and homophily effects included in one network model. The main effect controls the simple effect associated with the level of an attribute, whereas the homophily effect explains the co-consideration decision by the similarity or difference of two products in terms of their attributes. Table 1 generalizes the guidelines for creating explanatory networks in MRQAP for different types of attributes such as binary, categorical, or continuous. For the product attributes under (a)-(c), the strength of the tie X_{ij} of an explanatory network is determined by the corresponding attributes x_i and x_j associated with the linked products. Beyond product attributes, we may also introduce non-product related attributes (d). For example, the customer demographics can be included in the model to allow the prediction of technological impact in a completely new market following different customer profiles. However, multi-variable association techniques (e.g., correspondence analysis) should be applied first to express the similarity of the non-product related attributes as the coordinates of product points (x_i and x_j) in a geometric space.

Table 1: Constructing Explanatory Networks of Attributes

Configuration	Statistic		Network effect
(a) Binary product attributes			
Sum network	$X_{ij}=x_i+x_j$	(2)	Attribute-based main effect
Match network	$X_{ij}=I\{x_i=x_j\}$	(3)	Homophily effect
(b) Categorical product attributes			
Match network	Same as (4)		Homophily effect
(c) Continuous product attributes (standardized)			
Sum network	Same as (3)		Attribute-based main effect
Difference network	$X_{ij}=\lvert x_i-x_j\rvert$	(4)	Homophily effect
(d) Non- product related attributes			
Distance network	$X_{ij}=\lVert x_i-x_j\rVert_2$	(5)	Homophily effect

Note:
- $I\{\cdot\}$ represents the indicator function.
- $|\cdot|$ represents the absolute-value norm on the 1-dim space.
- $||\cdot||_2$ represents the L_2-norm on the n-dim Euclidian space.

From the method point of view, MRQAP is more accurate than the traditional regression model that requires independent assumption. This is because the network matrices often contain correlated observations in rows, columns or blocks, therefore the standard errors produced by a standard regression procedure is often inaccurate. In MRQAP, the rows and columns of a network matrix are permuted before estimating the model. This permutation procedure is repeated many times to give a distribution of the parameter estimates, where one can obtain unbiased standard errors and pseudo p-values.

3.5. Step 4 –Network prediction under technological change scenarios

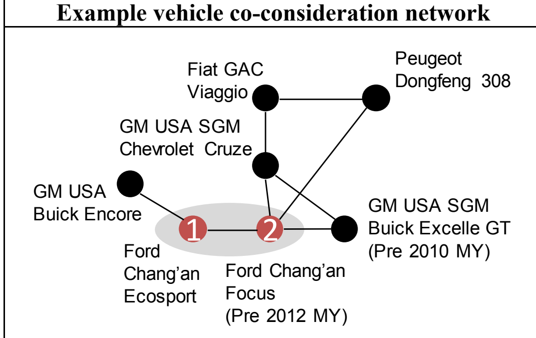
The MRQAP model obtained through Steps 1-3 will be used to predict the co-consideration relations between products under the technology influence. With the model established and scenarios created, the change of market competition induced by the new technology can be studied by changing the values of the corresponding product design attribute(s). As a result of the change of effect networks $\mathbf{X}$, co-consideration relations among products can be regenerated as the product association network $\mathbf{Y}$ following the function shown in Eqn.(1).

Table 3: Examples of network metrics used to quantify the properties of co-consideration network

Network metrics	**Definition**	**Interpretation in vehicle co-considerations**
Degree (d)	The number of edges of a node. The average degree of a node or a set of nodes is noted as ($\bar{d}$).	It reflects the number of competitions a vehicle has in the network. The average degree indicates the average number of co-consideration relations for a vehicle model or brand. As shown in Table 3, there are two Ford vehicles - one has degree $d_1 = 2$, and the other has $d_2 = 4$. Ford band has an average degree $\bar{d}_{ford} = \frac{6}{2}$.
Number of neighboring nodes (n)	The number of nodes directly connected to a node or a set of nodes in the same group. The average number of neighboring nodes is noted as ($\bar{n}$).	It measures the size of co-considered vehicle set for a vehicle or a vehicle brand, which implies the total number of competitors of a vehicle or a vehicle brand. As shown in Table 3, the Ford vehicle 1 has two co-considered vehicles, $n_1 = 2$. The Ford brand has 4 co-considered vehicles, $n_{ford} = 4$.
External degree (d')	The number of edges that connect a node to nodes in different groups. The average external degree of a set of nodes in the same group is noted as ($\bar{d}'$).	The external degree reflects the competition between brands. In Table 3, the Ford vehicle 1 only connects 1 non-Ford vehicle, thus $d_1' = 1$. Similarly, $d'_2 = 3$. As there are two Ford vehicles, the average external degree of Ford brand is therefore $\bar{d}'_{ford} = 4/2$.
Global cluster coefficient (c_G)	The proportion of closed triplets over all possible triplets (both open and closed) in a network. It is an indication of the clustering at the global level of a network.	c_G measures the cohesion or segmentation of the vehicle market. A low c_G network could have many open triplets (stars), i.e., a vehicle co-considered with many other unconnected vehicles; while a high c_G network has many closed triplets (triangles), i.e., any pair of three vehicles are co-considered with each other. Table 3 shows 3 closed triplets and 13 open triplets, thus c_G is low.
Local cluster coefficient (c)	A measure of the likelihood that two neighbors of a node are also neighbors with each other. The average local cluster coefficients of a given set of nodes is noted as ($\bar{c}$).	A vehicle with a high c is usually embedded in one cohesive vehicle segment where its competitors are also frequently being co-considered; a vehicle with a low c may have dissimilar competitors in many different vehicle segments, e.g., family sedans have higher c than that of crossover SUVs. In Table 3, Ford Chang'an Ecosport is not involved in any triangular relationships with other vehicles, so $c_1 = 0$.
Betweenness centrality (b)	The number of times a node acts as a bridge along the shortest path between two other nodes.	Vehicles with high betweenness centralities are most likely at the boundary between different market segments, e. g., a crossover SUV typically has higher betweenness than a classic sedan. In Table 3, to reach the other five vehicles, GM Buick Encore has to pass Ford Chang'an Ecosport 5 times, so $b_1 = 5$. Similarly $b_2 = 9.5$ indicates that Ford Chang'an Focus is likely at the boundary of a cluster, which is evident in Table 3.

Table 2: Illustrative example of network metrics in vehicle co-consideration network

Example vehicle co-consideration network



Network metrics
$d_1 = 2,\ d_2 = 4$
$n_1 = 2,\ n_{ford} = 4$
$\bar{d}_{ford} = \frac{6}{2},\ \bar{d}_{all} = \frac{16}{7}$
$d_1' = 1,\ d_2' = 3,\ \bar{d}'_{ford} = \frac{4}{2}$
$c_G = \dfrac{3}{13}$
$c_1 = 0,\ c_2 = \frac{1}{6}$
$\bar{c}_{ford} = \frac{1}{12},\ \bar{c}_{all} = \frac{3}{14}$
$b_1 = 5,\ b_2 = 9.5$

3.6. Step 5 – Evaluation of network structure metrics

Finally, in Step 5, the change of the network topology is characterized to provide insights for marketing strategies and design decisions. To quantify the change of network structure under different scenarios specified in Step 4, we adopt a set of network metrics as shown in Table 2. These metrics have different physical meanings in the context of product co-considerations, as described in the table using vehicles as examples. A set of metrics are used to characterize the global network (market-wide competition) such as $\bar{d}$, c_G, $\bar{c}$; while the remaining metrics N_c, d, $\bar{d}$, d', $\bar{d}'$, c, $\bar{c}$ and b are used to characterize the local network centered around a product node or a set of product nodes that belong to the same brand (or producer). Table 3 shows an illustrative example of metrics evaluation that supports the interpretation in Table 2.

4. CASE STUDY – VEHICLE CO-CONSIDERATION PREDICTIONS UNDER FUEL ECONOMY-BOOSTING TECHNOLOGIES IN CHINA'S MARKET

In this section, we use vehicles as an example to illustrate how the proposed approach can be used to forecast the impact of new technologies on customers' co-consideration of vehicles and market competitions. The case study is focused on China vehicle market to analyze the impact of introducing new technologies such as fuel economy-boosting technology and turbo technology. The obtained results are useful for understanding the underlying product attributes that determine customer co-consideration decisions, analyzing the competitions between different vehicle models and brands, and guiding auto companies to create marketing plans and product design strategies in preparation for new technology scenarios.

Various fuel economy-boosting technologies have emerged in recent years, including new combustion strategies, lighter weighting materials, series parallel hybrid, etc. In this paper, we first relate fuel economy-boosting technologies directly to the reduction of fuel consumptions to evaluate the market response. We then pick a specific fuel economy technology – the downsized turbo engine – that has impact on attributes including engine power, fuel consumption, turbo, and engine size, to predict the market effect of turbocharged vehicles relative to traditional gas-powered vehicles.

4.1. Step 1 – Data collection

Data used in this study is from the 2013 New Car Buyers Survey (NCBS) - China provided by Ipsos, a global market research firm. The data consists of 49,921 new car buyers' preferences over 389 unique vehicle models of the year 2013 in China's vehicle market. In survey, respondents were asked to list the car they purchased, the main alternative car they considered, and any other cars they considered before making the purchase decision. Due to the restriction from survey design, no respondent could list more than two other alternative vehicles in his/her consideration set even though the actual number of considered vehicles might be higher. The customer-desired product attributes (e.g., engine power, fuel consumption) are reported by customers in survey and verified by vehicle database. In addition, the data covers a diverse set of factors, including the customer demographics (e.g., age, income), and the customer perceived vehicle characteristics (e.g., youthful, sophisticated, business oriented). Our interest is to use the effect networks formed based on the associations of product and customer attributes to explain and predict the product associations in co-consideration.

4.2. Step 2 –Co-consideration network construction

The product co-consideration network is constructed based on the product co-consideration data in the aforementioned NCBS survey. To determine the existence of edge (link) between two nodes (vehicles) in the network, the $lift$ metric is adopted to normalize the co-occurrence frequency of products by the mere frequency of each product in the dataset. The $lift$ between vehicle model i and vehicle model j is calculated as

$$lift(i,j) = \frac{Pr\{coconsider\ \ i\ \ and\ \ j\}}{Pr\{consider\ \ i\} \cdot Pr\{consider\ \ j\}} \tag{6}$$

where Pr is the probability or the frequency of a vehicle model (i or j) is considered or a pair of vehicles (i and j) are co-considered by customers among all possibilities, calculated based on the collected consideration data. Note that consideration probability is different from market share that is directly associated with choice or purchase behavior. The $lift$ value indicates how likely two products are co-considered by a customer, normalized by the product popularity in the market. Eqn. (6) suggests that the relationship between two products is symmetric and reciprocal which results in a symmetric co-consideration relation matrix between each pair of products. Visualization of the network relations can be obtained but is omitted here due to the large number of vehicles (389) involved. In our constructed network, the cutoff point for the link value is set at $lift = 1$ [2].

4.3. Step 3 – MRQAP modeling

We employ MRQAP to analyze the underlying factors driving customers' co-consideration of vehicles using a set of explanatory effect networks created based on the associations of vehicle attributes and customer demographics. The result of MRQAP modeling using the NCBS data is reported in Table 4. In the established model, the explanatory networks are built from variables of all four different types as shown in Table 1. The two distance networks (*characteristics dist.* and *demographics dist.*) are built using the product coordinates derived from a joint correspondence analysis (JCA) between the non-product related attributes and the vehicle products. This is a unique feature of the proposed model, which integrates the JCA with MRQAP models, as detailed in [30].

From the results shown in Table 4, most attributes (except *fuel type match*, *power sum*, *fuel sum*, *engine size diff*, *engine size sum*, and *characteristics dist.*) are statistically significant at significance level of 0.05. This indicates the associations formed by these vehicle attributes are important in explaining customers' co-consideration behavior. All coefficients have expected signs: the positive coefficient before a *match network* (constructed based on binary or categorical attributes, e.g., *brand match*, *turbo match*) indicates vehicles sharing the same attribute categories are more likely to be co-considered (homophily); the negative coefficient for a *difference network* (constructed based on continuous attributes, e.g., *price diff*, *power diff*) indicates that the smaller the difference in attribute values, the more likely the two vehicles are co-considered (homophily); the positive coefficient for a *sum network* (constructed based on binary or

[2] Statistically, a $lift$ value equals 1 indicates that two vehicles are completely independent. A $lift$ greater than 1 indicates the two vehicles are co-considered more likely than expected by chance, and vice versa.

continuous attributes, e.g., *price sum*, *turbo sum*) implies that higher combined attribute values can increase the probability of vehicle co-considerations (attributed-based main effect); the negative coefficient for a *distance* network (constructed based on non-product related attributes, e.g., *characteristics dist.* and *demographics dist.*) shows that the further the two vehicles are away in the space of joint correspondence analysis, the less similar the non-product related attributes are shared by the two vehicles, and the less likely the two vehicles are co-considered by customers. The magnitude of the coefficient explains the level of importance of that effect network, indicating how close the structure of the attribute-based effect network is related to the vehicle co-consideration network. For example, *price diff.* has the strongest effect, meaning that the structure of the price difference network is the most related one to the co-consideration network. Similar to the traditional logistic regression, one can also interpret the coefficient in terms of the odds ratio. For instance, the coefficient of *brand match* informs that, there is 87% increase in the odds for same-brand vehicles to be co-considered, relative to two vehicles of different brands.

Table 4: Estimation Results of MRQAP Network Model

	Input attr. type	Coeff. β	$\exp(\beta)$	Pseudo P-Value
(Intercept)		-2.784	0.062	0.00
Vehicle Attribute Network				
Drivetrain match	Categorical	0.310	1.364	0.00
Gearbox match	Categorical	0.482	1.619	0.00
Fuel type match	Categorical	-0.070	0.933	0.56
Brand match	Categorical	0.625	1.868	0.00
Segment match	Categorical	1.299	3.666	0.00
Vehicle origin match	Categorical	0.284	1.329	0.00
Brand origin match	Categorical	0.619	1.857	0.00
Price diff.	Numerical	-5.633	0.004	0.00
Price sum	Numerical	1.747	5.735	0.00
Power diff.	Numerical	-1.791	0.167	0.00
Power sum	Numerical	0.430	1.537	0.37
Fuel consumption diff.	Numerical	-3.925	0.020	0.00
Fuel consumption sum	Numerical	0.170	1.185	0.59
Engine size diff.	Numerical	0.666	1.946	0.08
Engine size sum	Numerical	-0.105	0.901	0.82
Turbo match	Binary	0.350	1.419	0.00
Turbo sum	Binary	0.206	1.229	0.04
Perceived Vehicle Characteristics Network				
Characteristics dist.	Non-vehicle related	-0.469	0.626	0.07
Demographics Network				
Demographics dist.	Non-vehicle related	-0.856	0.425	0.00
Overall model fit				
Adjusted Pseudo- R^2: 0.49				

Different from a utility-based DCA model that only captures the main effect of product attributes, MRQAP compares different products in consideration by creating relational ties through associations of attributes. This capability is especially critical to our interest in understanding product competitions, because it allows us to answer questions related to the homophily effects, e.g., whether customers are more likely to co-consider similarly priced products.

To validate the MRQAP model's predictability, we regenerate the vehicle co-consideration network using the predicted probability of links given by Eqn. (1). After 100 network simulations, we evaluate the average prediction accuracy with two measures: a) *sensitivity*, the percentage of correctly predicted edges among all actual connections; and b) *specificity,* the percentage of missing edges that were correctly predicted as such [31]. From Table 5, it is observed that the model can maintain a specificity at 0.93 and a sensitivity at 0.253. The results imply that the model predicts more accurately when two vehicles are not being co-considered than they are actually co-considered. This is mainly due to the low density in the observed co-consideration network, where over 90% of possible edges are missing.

Table 5: Prediction accuracy of MRQAP model. Evaluated by the mean of 100 simulated networks. The standard deviations are shown in parentheses.

Predicted / Actual	Connected	Not connected	Accuracy
Connected	1629 (33.5)	4820 (33.5)	Sensitivity: 0.253 (0.0052)
Not connected	4818 (62.2)	64199 (62.2)	Specificity: 0.930 (0.0009)

4.4. Step 4 – Scenario formulation and network prediction

To examine the impact of technology change on market response, we make the following assumptions: 1) The market response only changes as a result of introducing new technologies, e.g. *fuel consumption* variable in the MRQAP model, while the rest of the variables are unaffected; 2) The target population of customers remain the same as the profile distribution drawn from the NCBS dataset; 3) The new technology is only introduced for a specific set of vehicles in the market, and designs of other vehicles do not change. The

Table 6: Predicted metrics averaged by 100 network simulations, the standard deviations are shown in parentheses.

Full vehicle network			Toyota				Ford			
c_G	$\bar{c}$	$\bar{d}$	N_c	$\bar{c}$	$\bar{d}$	d'	N_c	$\bar{c}$	$\bar{d}$	d'
0.17 (0.0029)	0.18 (0.0028)	33.14 (0.41)	266.32 (7.43)	0.16 (0.0066)	32.06 (1.21)	499.95 (20.15)	197.3 (8.49)	0.15 (0.003)	32.57 (1.75)	277.63 (14.64)

following "what if" scenarios are considered for the vehicle problem.

- Scenario 1: We study the general effect of various fuel economy-boosting technologies by varying *fuel consumption* from 100% to 50% of its original value (at a rate of 5%).
- *Scenario 2*: We study specifically the effect of a downsized engine with a turbocharger installed. By maintaining the same power output, the turbocharged version reduces *fuel consumption* by 20% and *engine size* by 30% [32].

Note that these two scenarios are proposed for the purpose of exploratory study. This means the scenario may not be realistic, e.g., the reduction of fuel consumption to 50% of the current capacity is difficult to achieve. Our goal is to demonstrate the potential impact the change of product attributes may bring. Besides of these scenarios, we further assume such technologies are brought by two specific motor companies, Toyota and Ford respectively. We are particularly interested in these two brands because of their prominent difference in the number of vehicle models available in China market which would result in a contrast of analysis results. For example, our data indicates that Ford has 9 different vehicle models in China market, while Toyota has 17 models. Toyota has been the fuel economy leader for many years, while Ford is an early adopter of the turbocharged engines across its lineup. Under the above scenarios, we investigate the impacts from two different perspectives, the full vehicle co-consideration network from a global perspective, and the networks centered around Toyota vehicles and Ford vehicles [3] respectively from a local perspective. The behaviors of the two local network (centered around Toyota and Ford) are considered independently. The supporting evidence for this assumption is that there are no strong links (measured by lift values) between Toyota and Ford vehicles in the constructed vehicle co-consideration network.

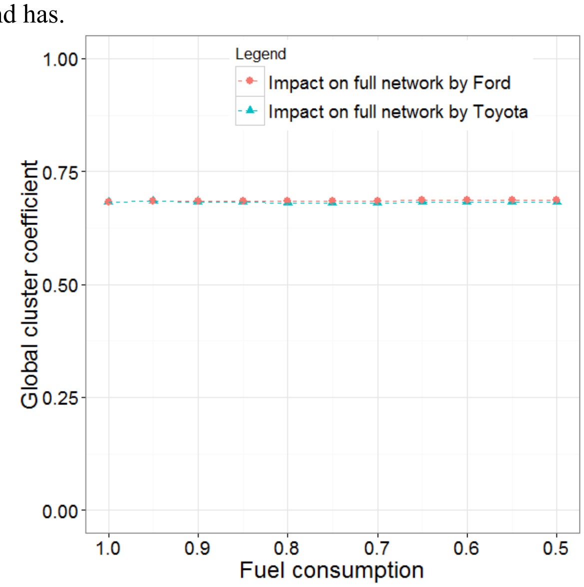
Since the network generation process with the MRQAP model is probabilistic in nature, before performing detailed scenario analysis, we evaluate the variation of predicted networks based on some of the proposed network metrics (global cluster coefficient c_G, average local cluster coefficient $\bar{c}$, average degree d, and external degree d'). Table 6 lists the corresponding averages and standard deviations of each network metric based 100 network simulations. Both the full vehicle co-consideration network and networks centered around a brand (Toyota and Ford respectively) are analyzed. For example, the average value of the global cluster coefficient of 100 simulated networks is 0.17, with the standard deviation 0.0029. The small standard deviations in Table 6 imply our model is capable of predicting the vehicle co-consideration network consistently.

[3] We only focus on vehicles with Toyota or Ford brand. This means Lexus, for example, even though belonging to Toyota company, it is not within our scope of analysis.

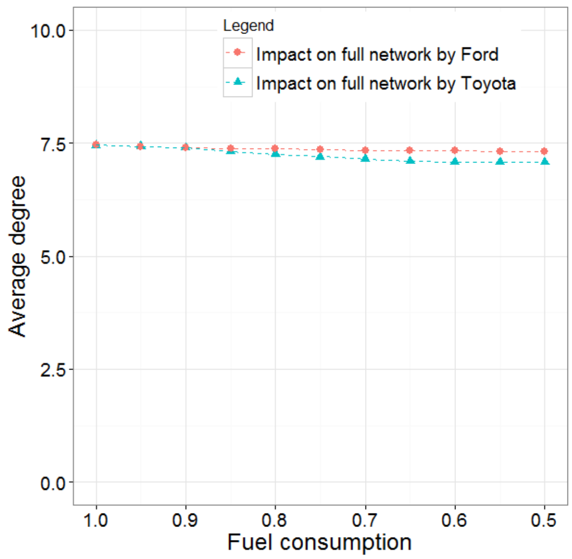
4.5. Step 5 – Network evaluation under technological impact

The purpose of this step is to evaluate and interpret the change of network structures due to the technological impacts. We first apply Scenario 1 where fuel economy-boosting technologies are adopted by Toyota and Ford, respectively. In the full network (market) analysis, little change has been found for global cluster coefficient c_G when fuel consumption decreases (Fig. 5(a)). There is a slight decrease in the average degree $\bar{d}$, from 7.46 to 7.07 when Toyota reduces fuel consumption to half, and to 7.32 when Ford does the same (Fig. 5(b)).

These results suggest that the application of fuel economy-boosting technologies by a single company may not affect the overall market segmentation, but may slightly reduce the competitions in the whole market. Larger impact on $\bar{\boldsymbol{d}}$ (with faster decreased curve) is observed when Toyota applies the fuel reduction technology than when Ford does. This is because the market contains 17 Toyota vehicle models but only 9 Ford models. This implies that the market impact that one brand brings largely depends on the number of vehicle models that brand has.



(a) Global cluster coefficient (c_G)



(b) Average degree ($\bar{d}$)

Figure 5: The impact of fuel consumption on full network

When examining the local impact on a specific vehicle brand, we find that even though Toyota offers more vehicle models in the market, Ford vehicles have more co-considered vehicles on average (see Figure 6(a)), and more co-consideration relationships with other vehicle brands on average (see Fig. 6(b)). These results imply that in the 2013 China market, on average a Ford vehicle may have more competitors than a Toyota vehicle does.

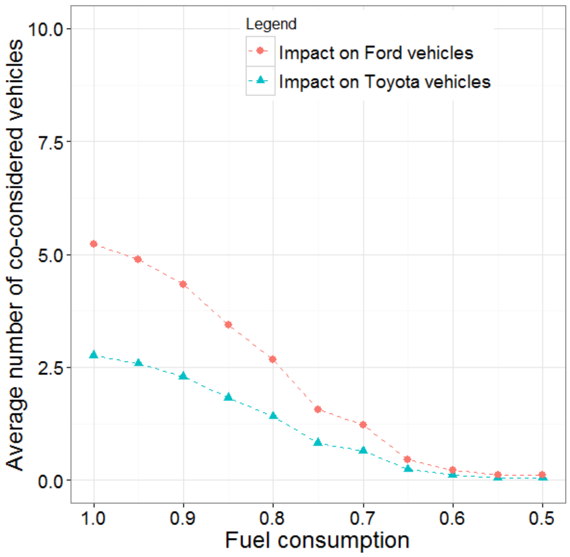
The declining trend of the two lines in Fig. 6(a) shows that the number of vehicles being co-considered decreases for both Toyota vehicles and Ford Vehicles, respectively. For example, the number of Ford's competitors reduces from 22 to 3 when fuel consumption reduces to 70% of its original specification, and is even 0 when the fuel consumption reaches 50%. This means, once Ford decides to adopt the fuel reduction technology, its vehicles would become more distinguishable on the market, based on the assumption that the rivals' vehicle configurations are unchanged. For example, at 90% fuel reduction point, Toyota GAIG Highlander is no longer Ford Edge's rival; Honda Guangzhou Accord would not compete against Ford Changan Mondeo any more.

In Fig. 6(b), the average external degree $\overline{d'}$ of Toyota and Ford vehicles both decline, respectively, implying vehicles from Ford or Toyota would be less likely to be co-considered with vehicles from other companies when the fuel consumption decreases. From the similar decreasing trends in Fig. 6(a) and (b), one can infer that when one competing vehicle is removed (or not further co-considered with Ford or Toyota vehicles) in Fig. 6(a), only one edge is taken away in Fig. 6(b). This means most of the removed edges corresponded to one-on-one competition before applying the changes. It is observed from Figures 6(a) and (b) that while fuel consumption decreases, the number of vehicles co-considered for Ford decreases faster than that of the Toyota vehicles. This indicates that the impacts of fuel reduction technology on Ford vehicles are more significant than the effect on Toyota vehicles in China's market.

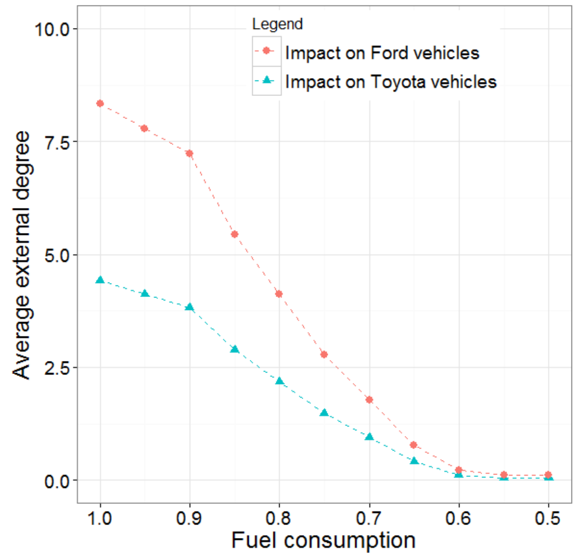
Moreover, it is observed that the average number of edges connected to Toyota vehicles or Ford vehicles, measured by average degree, decreases as fuel economy improves (see Fig. 6(c)). The declining curves indicates that the number of edge taken away is more than the number of edge added. Together with the observations in Figures 6(a) and 6(b), it can be inferred that the edges within Toyota or Ford vehicles do not change much. This observation is confirmed by the data. The reason is due to the fact that the edge structures in the two brand networks are predicted using the MRQAP model presented in Table 4. When we vary the value of the *fuel consumption* variable, the effect networks of *fuel consumption diff.* and *fuel consumption sum* will change, accordingly. However, the attribute-based main effect represented by the *fuel consumption sum* is non-significant, whereas the homophily effect represented by the *fuel consumption diff.* dominates the structural changes, as shown by its model coefficient (-3.925). This means when the fuel consumption for a vehicle is changed to a level significantly lower than that of the competing vehicles, the co-consideration edge between them will disappear as the effect of homophily. However, the internal edges within a brand largely remain unchanged, because the vehicles within the same brand are similarly affected by the new technology and the difference of fuel consumption between two vehicles do not change significantly.

In Fig. 6(d), the average cluster coefficient $\bar{c}$ of Toyota vehicles are higher than that of Ford vehicles before fuel consumption decreases. The high $\bar{c}$ implies that the competitors of Toyota vehicles are highly connected, where three-way competitions (closed triplets) are frequent to see. In contrast, Ford vehicles attract more diverse competitors which are less similar to each other. Under the change of fuel consumption, $\bar{c}$ curves of Ford vehicles and Toyota vehicles decrease, respectively. The $\bar{c}$ value of Ford vehicles drops to 0 when fuel consumptions reduces to 50%, as no co-considered vehicles present at that point (see Fig. 6(a)), and no three-way competition exists among the Ford vehicles. The fluctuations in $\bar{c}$ curves are due to the structural variations of edges both outside to competing vehicles and inside among Ford vehicles. For example, a big rise in $\bar{c}$ at 80% level point can be explained by the new connection between Ecosport and New Focus. The new edge makes the Ford Changan Ecosport, Ford Changan New Focus, and Classic Focus form a new triangular competition (closed triplet), contributing largely to the high $\bar{c}$ of Ford vehicles. The curve falls back at 75% level point, because the triangular competition formed by Ford Explorer, Toyota FAW Land Cruiser Prato, and Jeep Grand Cherokee is broken, resulting in Grand Cherokee be the only competitor against Explorer.

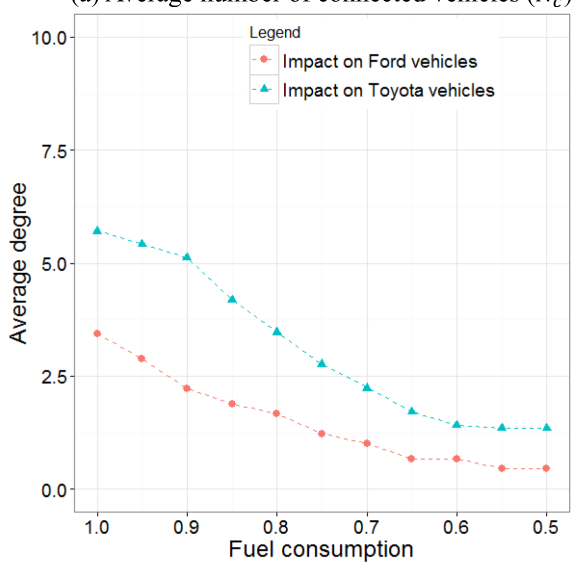
In Scenario 2, we investigate the impact of turbo technology on vehicle co-consideration relationships. The results in Table 7 show the combined effects due to the change of turbo dummy (from 0 to 1), fuel consumption (decreased by 20%), and engine



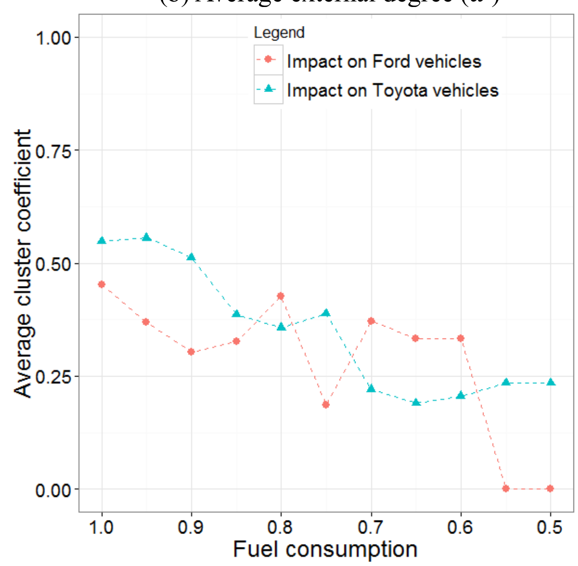
(a) Average number of connected vehicles ($\overline{N_c}$)



(b) Average external degree ($\overline{d'}$)



(c) Average degree ($\bar{d}$)



(d) Average cluster coefficient ($\bar{c}$)

Figure 6: The impact of change of fuel consumption on the topology of Toyota and Ford Local Networks

size (decreased by 30%)[4]. We find that with the turbo technology applied, the external degree d' decreases for Toyota vehicles from 75 to 10 and Ford vehicles from 25 to 11, respectively, implying the declines of external competitions. As shown in Table 7, it is predicted that 40 other vehicle models (i.e., 47-7=40) are no longer co-considered by customers after Toyota applies turbo technology. Similarly, the co-considered vehicles with Ford vehicles are reduced by half (22 to 11).

Table 7: Prediction of turbo technology impacts on Toyota vehicles and Ford vehicles

Network metrics	Toyota		Ford	
	Without turbo	With turbo	Without turbo	With turbo
$\bar{c}_{all}$	0.68	0.68	0.68	0.67
$\bar{d}_{all}$	7.46	7.14	7.46	7.39
N_c	47	7	22	11
d'	75	10	25	11
$\bar{c}$	0.55	0.20	0.45	0.49
$\bar{d}$	5.71	2	3.44	1.89

[4] For vehicles already have a turbo installed, no changes in attributes are conducted.

Although the number of co-considered vehicles decreases for both Toyota and Ford respectively, the cluster coefficient $\bar{c}$ of Ford vehicles increases after Ford applies the turbo technology. This implies that the adoption of turbo by Ford may increase the connectivity (competitions) among Ford and its competitors. However, in the Toyota vehicles, $\bar{c}$ decreases from 0.55 to 0.2. Such reverse trends between Toyota and Ford indicate that same technology adopted by different vehicle brands may have diversified effects on the market response.

5. CONCLUSION

In this paper, an analytical approach based on network analysis is developed to facilitate the study of customers' co-consideration behaviors and market competitions. Specifically, the MRQAP is employed to provide quantitative prediction of customers' co-consideration relations as a function of various effect networks (match, sum, difference, and distance) created by associations of attributes. By mapping new technology to the change of product design attributes, the proposed approach enables the prediction of technology impact on product co-consideration relations. The generated results are useful for understanding the customer co-considerations decisions and product competitions, which is crucial to identifying marketing strategies and introducing product differentiations in engineering design.

Two scenarios of technology application – the general fuel economy-boosting technologies and a specific turbo engine technology – are investigated. The insights drawn from the case study using the collected data in China vehicle market are summarized as follows. First, the adoption of new technology by a single brand may not change much the structure of vehicle co-considerations on the whole market. Second, new technology may lead to less competitors and less competitions among a vehicle brand. Third, the three-way competitions can be mitigated if fuel economy-boosting technologies are applied. Fourth, the same technology may bring different impacts if adopted by different brands. All these insights can help vehicle producers make decisions on new technology adoptions.

The developed network model can handle complex relational data whose properties cannot be reduced to only the attributes. This capability is crucial when examining problems like co-consideration decisions where the relationship (such as similarity) between two products are possibly more important than the attributes of single products. The structure of the MRQAP model allows the evaluation of homophily effect and attribute-based main effect simultaneously, which is ideal for identifying key product attributes that drive customer co-consideration decisions. This is a unique feature of network-based models, which differentiates from DCA that directly uses attributes of products and/or customers as predictors. It should be noted that the derivation of DCA strictly follows the utility theory which assumes consumers make decisions by maximizing their intrinsic utilities. From this perspective, DCA is more appropriate for analyzing purchase decisions given the consideration set of products, whereas network models are better suited for relationship analysis such as co-considerations and competitions of products. The network-based approach and the DCA approach can be complementary to each other, where a two-stage model using network analysis to compose consideration sets and subsequently using DCA to estimate probability of choice may be considered.

This research is a part of a larger effort to explore and address various challenges associated with complex customer-product interactions via network analysis. The main contribution of this paper is to propose a network-based framework to quantitatively evaluate the change of customers' co-consideration decisions under technology push. Methodologically, this work extends the network model as a unified statistical inference framework for predicting customer-product relations. In the future, other modeling approaches, e.g., Exponential Random Graph Models [19, 33] will be examined to model the product co-consideration network by considering not only the product attributes, but also other underlying factors like social influence. Efforts will also be devoted to the robustness check of the proposed approach under a variety of settings in network modeling, e.g. various sizes of networks, alternative measures of similarities besides *lift*, and sensitivity of consideration set size on network links, etc. Though our case study focuses on the design of fuel-efficient vehicles, the methodology can be extended to other technology driven single or product family designs. Network models may also be integrated into a game-theoretic model for the study of competitive marketing strategies by relaxing the assumption of unchanged configuration of rivals' vehicles.

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