

Research on the Dynamic Evolution Mechanism of Brand Competition Relationship Networks Based on Stochastic Actor-Oriented Models

Mei H. Zuo^{1,*}
Huang L. Lai²
Zhou Y. Liang³
Jia Y. Zuo⁴

*Corresponding author

¹Associate professor, Huizhou University, Huizhou, China, zuomeihua123@126.com

²Undergraduate student, Huizhou University, Huizhou, China, 2309175236@qq.com

³Laboratory technician, Guangdong University of Technology, Guangzhou, China, liangzy@gdut.edu.cn

⁴Undergraduate student, Southern University of Science and Technology, Shenzhen, China, jyzuo05@gmail.com

ABSTRACT

To explore the dynamic evolution of brand competition networks and effectively help private brand firms manage production and operation risks, this study, drawing on consumers' real-time implicit preferences, uses the Stochastic Actor-Oriented Model and analyzes platform consumers' clickstream data to build a dynamic brand competition network. It also applies the Social Network Analysis software SIENA to examine the driving mechanisms of individual brand attributes and network structural attributes on network evolution. The study finds brands with common competitive targets, similar age-group consumers or higher sales are more competitive, while those targeting the elderly, serving high-tier members or with similar membership tiers have lower competition probability. It provides references for brand strategy optimization and customer management, future research may analyze preference disparities across click behaviors.

Keywords: Online marketplace, dynamic brand competition, clickstream data, network analysis, stochastic actor-oriented model.

INTRODUCTION

The Research Report on the Development of Chinese Private Brands (2024-2025) shows that from 2022 to 2024, the average annual number of newly developed private brand products by retailers increased from 83 to 142, presenting a trend of rapid expansion. Meanwhile, existing research also indicates that private brands commonly adopt the competitive strategy of product diffusion (He *et al.*, 2022). Product diffusion can not only maintain the loyalty of existing consumer groups but also attract the consumer groups of competitors, thereby increasing their own market share and profitability, and thus enhancing their competitive intensity in a specific market segment (Zou *et al.*, 2020). However, product diffusion may lead to the cannibalization effect within a brand, meaning that products offered by the same brand may be regarded as substitutes (Shriver and Bollinger, 2020). A strong cannibalization effect gives rise to the long-tail phenomenon in the sales distribution of products within a brand (Park *et al.*, 2020, Brynjolfsson *et al.*, 2020). This phenomenon increases a brand's production and inventory costs, thereby affecting the brand's overall competitive strength.

Therefore, how to accurately identify brand competitive relationships, systematically analyze influencing factors, and formulate scientific production strategies based on these analyses has become the core breakthrough point for private brands to enhance their market competitiveness. Only by quantitatively analyzing the dynamic evolution patterns of the competitive relationship network and deeply exploring the key factors influencing brand competitive behaviors can we provide strong support for the product layout, resource allocation, and strategic planning of private brands.

This study focuses on the field of brand competition. By capturing clickstream data that reflects consumers' implicit preferences, it constructs a visual network of brand competitive relationships. Based on the theories of implicit preference and brand competition network, the study innovatively introduces the Stochastic Actor-Oriented Model. It approaches the topic from two dimensions: the attributes of consumer behavior and the social network attributes to which brands belong, systematically analyzing the key factors influencing the dynamic evolution of brand competition intensity. The aim is to provide theoretical support and practical paths for the sustainable construction of brand competitive advantages.

THEORETICAL BACKGROUND

Implicit Preferences and Brand Competition

Building on Ringel and Skiera (2016), brand operators use clickstream data to visualize competitive networks and define market segments, yet existing studies overlook the dynamic nature of consumer implicit preferences. Human dynamics theory

suggests preferences evolve dynamically, diminishing marginally with repeated purchases, but most research remains static. In information systems, while Ravindran *et al.* (2015) analyze network dynamics via time-window segmentation, this approach risks missing structural changes and introduces network autocorrelation—originally from spatial statistics (Wang *et al.*, 2018)—with few studies exploring its causes. Moreover, the interdependence between consumer behaviors and social network structures in brand-consuming groups lacks theoretical and practical integration, hindering firms from leveraging implicit preferences for competitiveness. Network research (Steglich *et al.*, 2010) emphasizes studying the co-evolution of social behaviors, individual actions, and network structures. Thus, this study integrates the Stochastic Actor Model with private brand competitive network visualization using clickstream data, aiming to enhance brand competitiveness by capturing dynamic preference shifts.

Implicit Preference and Network Theory

Building on prior research, this study integrates consumer online behavior and network theory to explore competition. We aim to construct brand competition relationship network using consumer clickstream data, and analyze how the co-evolution of consumer behavioral and network structural attributes impacts network. Clickstream data, which objectively records consumers' online browsing paths (Bucklin and Sismeiro, 2009), has been used in previous studies to predict product selection likelihood (Moe and Fader, 2004) and construct brand competition networks (Ringel and Skiera, 2016). Given its variation across different consumer demographics (Zuo *et al.*, 2023), we focus on age and membership level as behavioral attributes.

Network analysis offers unique insights into social relationship evolution (Wu *et al.*, 2017). However, traditional static methods relying on density, centrality, and structural holes (Markóczy *et al.*, 2013, Paruchuri, 2010) struggle to explain network dynamics. Network evolution involves the creation and dissolution of relationships, influenced by both structural factors like reciprocity (Snijders, 2017) and actor attributes. In our study, brand competition is modeled as a social relationship network, with consumer click behaviors driving changes. We adopt a network dynamic analysis approach, using the SAOM to incorporate both network and consumer attributes, and estimate model parameters with the SIENA tool. This enables us to comprehensively capture the evolution of brand competition networks, providing practical implications for brand strategy and customer relationship management.

DATA SOURCES AND NETWORK CONSTRUCTION

Data Sources

We sourced desensitized clickstream data from a major Asian B2C e-commerce platform, focusing on 10 weeks of consumer behavior within a single product category. The dataset includes 6554984 records from 54405 consumers browsing 2688 products across 86 brands. Among these, 6202 consumers made 6982 purchases involving 529 products from 52 brands. Key statistics are presented in Table 1. Given that purchasing behavior more accurately reflects market demand than browsing, we limited our initial analysis to clickstream data from the 52 purchased brands.

Table1: Descriptive statistics of dataset

Click volume	No. of consumers with click behavior	No. of products clicked	No. of brands clicked
6554984	54405	2688	86
Purchase volume	No. of consumers with purchase records	No. of products purchased	No. of brands purchased
6982	6202	529	52

Network Construction

Construction of brand competition relationship matrix

A brand consideration set is constructed based on individual consumers, where the consideration set refers to the possibility of a brand being considered (Wang *et al.*, 2013). To reflect the dynamic process of brand competition intensity, this study divides the clickstream data into time windows, partitioning the 10-week clickstream data into 9 time windows with each two-week period as a sample cycle (Zuo *et al.*, 2020). In the same time window, brands that co-occur in consumers' clickstream data are regarded as having competitive relationship (Zuo *et al.*, 2019). The joint consideration set refers to aggregating individual-level consideration sets. The construction process of the aggregation matrix is shown in Equation (1). In the matrix, each element represents the number of consumers who consider brands as mutually substitutable within the same time window. Once this consideration set is constructed, it can reveal the competitive market structure. In Equation (1), N_{jkt} represents the number of consumers who consider both brand j and k simultaneously in the t^{th} time window. Let I denote the set of consumers, and i represents a specific consumer. For example, if consumer i considers brand j in the t^{th} time window, then $L_{ijt} = 1$; otherwise, $L_{ijt} = 0$. Similarly, $L_{ikt} = 1$ indicates consumer i considers brand k in the t^{th} time window; otherwise, $L_{ikt} = 0$.

$$N_{jkt} = \sum_{i \in I} L_{ijt} \times L_{ikt} \quad (1)$$

However, in the matrix constructed by Equation (1), there is a discrepancy between the average number of consumers considering brands at the individual consumer and brand level. To eliminate this discrepancy, this study employs an asymmetric binary matrix N_{jkt}^* for transformation. The specific process is shown in Equation (2), where all parameters have the same meanings as in Equation (1).

$$N_{jkt}^* = \frac{\sum_{i \in I} L_{ijt} \times L_{ikt}}{\sum_{i \in I} L_{ikt}} \quad (2)$$

Visualization of brand competition relationships

Based on the matrix constructed from Equation (2), we employ social network tools (Rappuoli & Aderem, 2011) to identify the brand competition relationship matrix across different time windows. The Louvain community detection method is used to visualize brand competition relationships. This method offers the following advantages in visualization: Firstly, compared to the K-means clustering method, it does not require the pre-determination of the number of clusters, thereby making the identification results more objective. Secondly, in comparison to other visualization methods, this approach yields higher distinctiveness among the identified communities. Given the large number of brand competition relationship networks across the nine time windows, this study presents the identification results by taking the first time window as an example, as specifically illustrated in Figure 1. In the figure, nodes represent brands, with the size of each node indicating its market share, the color of the node representing the specific market segment it belongs to, and the thickness of the arrows indicating the intensity of competition between brands.

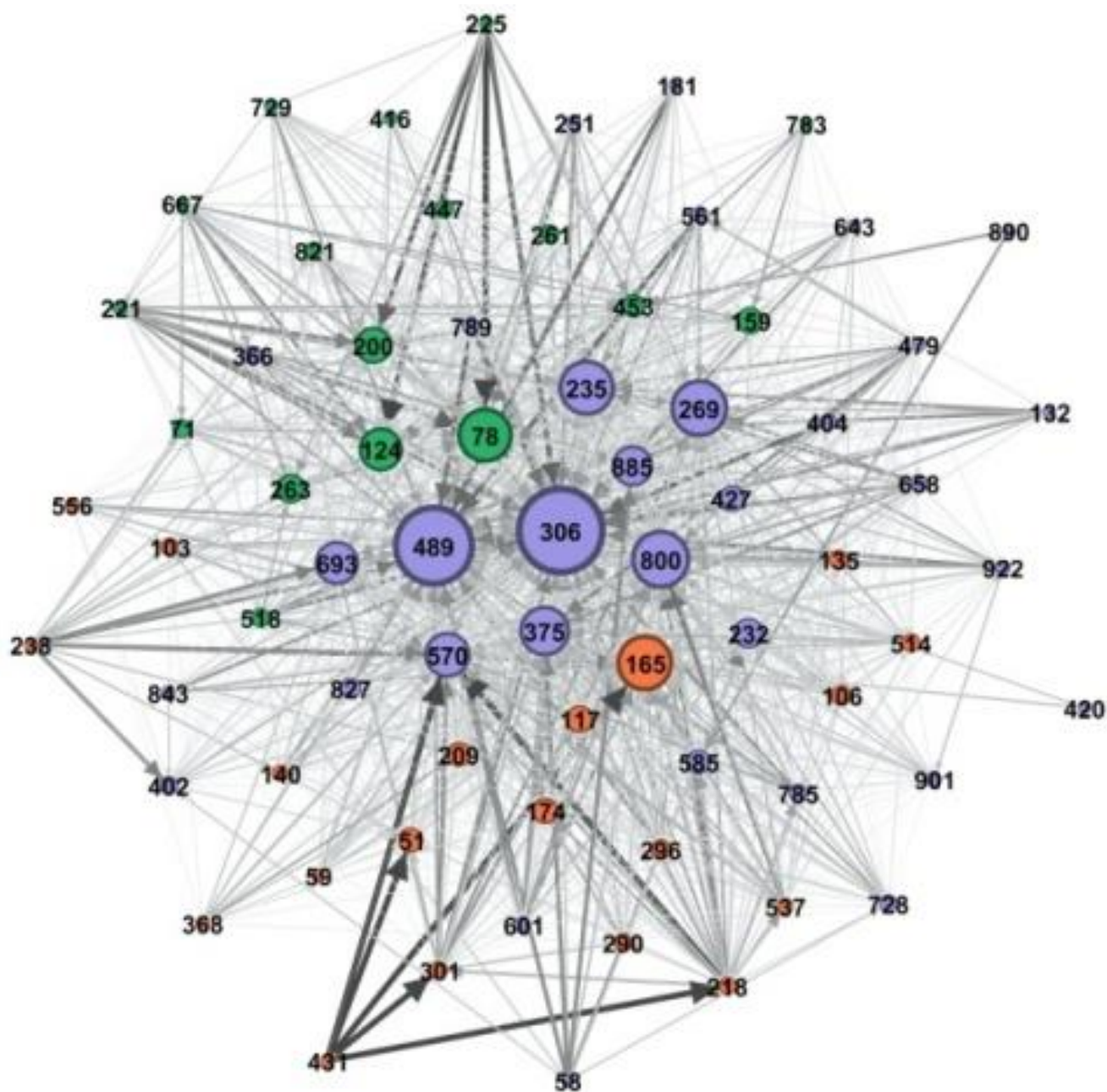


Figure 1: Asymmetric competition between brands in the first time-window

STOCHASTIC ACTOR-ORIENTED MODEL

Drawing on Snijders (1996), the SAOM analyzes network structural dynamics by positing that nodes optimize connections through out-degree control, driving network formation and evolution. As actors make decisions to maximize social utility (Snijders *et al.*, 2010), the model regresses network changes on actor attributes, structural properties, and random variables. Implemented via Monte Carlo Markov Chain simulation, the algorithm generates synthetic network and behavioral data, iteratively refining parameters until simulated outcomes converge with empirical statistics. Parameter significance is evaluated using t-tests, ensuring robust estimation of dynamic processes.

Establishing the Stochastic Actor-Oriented Model

SAOM divides the stochastic evolution process representing the network into two stochastic subprocesses consisting of four components, as shown in Table 2, namely: (1) the objective function $f_i(x^0, x, v_i, \omega_{ij})$, which represents the overall structural effect preferred by the actor i among all possible network configurations and the constraints imposed, wherein the objective function comprises two parts—the network objective function $f_i^{\text{net}}(x^0, x, v_i, \omega_{ij})$ and the behavioral objective function $f_i^{\text{beh}}(x^0, x, v_i, \omega_{ij})$, with their specific expressions given by Equations (3) and (4); (2) the rate function $p_i(x^0, x, v_i, \omega_{ij})$, which indicates the opportunities for the actor i to alter network relationships, and similarly, the rate function also includes two parts—the network rate function $p_i^{\text{net}}(x^0, x, v_i, \omega_{ij})$ and the behavioral rate function $p_i^{\text{beh}}(x^0, x, v_i, \omega_{ij})$, with their specific expressions provided by Equations (5) and (6).

Table 2: Schematic diagram of model composition

	Change rate	Change rule
Network change	Network rate function	Network objective function
Behavior change	Behavior rate function	Behavior objective function

$$f_i^{\text{net}}(x^0, x, v_i, \omega_{ij}) = f_i^{\text{net}}(x^0, x, v_i, \omega_{ij}) = \sum_k \beta_k^{\text{net}} s_{ik}^{\text{net}}(x^0, x, v_i, \omega_{ij}) \quad (3)$$

$$f_i^{\text{beh}}(x^0, x, v_i, \omega_{ij}) = f_i^{\text{beh}}(x^0, x, v_i, \omega_{ij}) = \sum_k \beta_k^{\text{beh}} s_{ik}^{\text{beh}}(x^0, x, v_i, \omega_{ij}) \quad (4)$$

In Equations (3) and (4), x^0 represents the current network state, x denotes the potential new state of the network, v_i signifies the individual attribute characteristics of the actors, and ω_{ij} indicates the dyadic relationship features among actors. $s_{ik}^{\text{net}}(x^0, x, v_i, \omega_{ij})$ represents the effect function influencing structural changes in the network, with its specific form and meaning detailed in Table 3. $s_{ik}^{\text{beh}}(x^0, x, v_i, \omega_{ij})$ denotes the effect function driving changes in actors' behavioral attributes, and the form and interpretation of these behavior attribute effects are also provided in Table 3. β_k^{net} and β_k^{beh} represent network and behavioral statistical parameters, which require estimation based on actual statistical data. A positive parameter value indicates that the effect function has a positive influence on network or behavioral evolution; a negative value suggests a negative impact; similarly, a zero value implies no effect on the study of network or behavior.

$$P\{X(t) - x^0\} = p_i^{\text{net}}(x^0, x, v_i, \omega_{ij}) = \frac{\exp(f_i^{\text{net}}(x^0, x, v_i, \omega_{ij}))}{\sum_{x \in C(x^0)} \exp(f_i^{\text{net}}(x^0, x, v_i, \omega_{ij}))} \quad (5)$$

$$P\{X(t) - x^0\} = p_i^{\text{beh}}(x^0, x, v_i, \omega_{ij}) = \frac{\exp(f_i^{\text{beh}}(x^0, x, v_i, \omega_{ij}))}{\sum_{x \in C(x^0)} \exp(f_i^{\text{beh}}(x^0, x, v_i, \omega_{ij}))} \quad (6)$$

In Equations (5) and (6), actor i has the opportunity to alter, modifying the existing tie variable x_{ij} , thereby resulting in a new state x , with $x \in C(x^0)$. The meanings of other parameters remain consistent with those in Equations (3) and (4).

Parameter Estimation Results

To analyze network evolution, we included key parameters in the SAOM and used RSiena for estimation (Table 3). Rate parameters (Periods 1–4) measure per-node competitive relationship changes across network transitions. Notably, network 1→2 showed the highest change intensity. T-statistics confirm model convergence and robust findings:

- 1) Reciprocity negatively impacts network evolution, while triadic closure has positive effects.
- 2) Higher consumer membership levels or more homogeneous membership groups reduce competitive relationship likelihood.
- 3) Younger consumers or more homogeneous age groups increase competitive dynamics.
- 4) Brands with higher sales volumes are more prone to competitive interactions.

Table 3: Estimation results of Stochastic Actor Oriented Model

Variables	Parameter estimates	Standard error	t-statistic
Rate parameter period 1	5.1890	0.3575	—
Rate parameter period 2	4.7310	0.3390	—
Rate parameter period 3	4.6436	0.3466	—
Rate parameter period 4	4.9696	0.3617	—

Out-degree (density)	-5.9437**	0.4609	0.0422
Reciprocity	-1.1491*	0.1657	0.0514
Transitive triplets	0.3921**	0.0329	0.0455
Membership Level	-1.2656**	0.3719	-0.0313
Membership Level Similarity	-0.3844***	0.2494	0.0065
Age	-0.2317**	0.1839	0.0187
Age Similarity	0.6493**	0.1769	-0.0335
Sales Num	0.6930**	0.0843	0.0223

Note: $t\text{-statistic} = (\text{observed value} - \text{sample mean}) / \text{standard error}$. When the absolute value of the t -statistic is less than 0.1, it indicates parameter convergence during estimation, with * denoting $P < 0.1$, ** denoting $P < 0.05$, and *** denoting $P < 0.01$.

CONCLUSION

Research Findings

This study employs SAOM and social network analysis to model brand competition dynamics on e-commerce platforms, constructing a competitive network from clickstream data to analyze evolutionary drivers. Key findings reveal a triadic closure effect where brands sharing a competitive link with a third brand are prone to direct competition, alongside influential factors: similar consumer age demographics and higher sales volumes enhance competitive relationships, while older consumer groups, higher membership tiers, and homogeneous membership levels mitigate such competition.

Managerial Implications

This study provides actionable insights for brand strategy and customer relationship management. For strategy management: first, leverage the transitivity of competitive relationships to analyze network connections, identify potential rivals, and deploy differentiated strategies (e.g., product specialization or price tiering) — if Brand A competes with B and C, anticipate a B-C competitive link and avoid homogeneity. Second, target niche market segments to bypass direct competition with same-sales-tier leading brands, using low-competition-sensitivity products in mid-low sales circles as barriers. Third, adopt co-branded marketing or bundled products to drive competition among younger demographics, while emphasizing product differentiation (over price wars) for middle-aged/elderly groups to leverage their low brand-switching propensity.

For customer relationship management: first, offer exclusive private-label benefits (e.g., customized pre-sales, priority after-sales) to high-tier members to raise switching costs, and design tiered incentives (e.g., point redemptions) to cultivate low-tier members' consumption habits. Second, construct a competitive risk early-warning model by integrating customer age and membership data — for example, trigger alerts when brand customer bases have < 5 years average age difference and $> 70\%$ membership tier similarity, enabling prompt adjustments to promotion strategies or benefits to prevent customer loss.

Research Limitations

This study, while contributing to the understanding of online brand competition network evolution, has limitations: it relies on single-platform data, limiting generalizability due to variations in e-commerce platforms' competition logics and user behaviors; it does not deeply analyze click behavior-based preference differences, affecting accuracy in judging consumer brand attitudes; and the model lacks integration of external factors like economic conditions and policies, with assumptions differing from real-world corporate decisions. Future research should focus on multi-platform data integration, in-depth click behavior analysis, inclusion of external factors, and model optimization.

ACKNOWLEDGMENT

The work is supported by the Basic and Applied Basic Research Foundation of Guangdong (Grant No.2022ZX163) and the 2024 Provincial College Students' Innovation and Entrepreneurship Project (Project No.: S20241057709)

REFERENCES

- Brancatelli, C., Fritzsche, A., Inderst, R., & Otter, T. (2022). Measuring income and wealth effects on private-label demand with matched administrative data. *Marketing Science*, 41(3), 637-656. <https://doi.org/10.1287/mksc.2021.1334>
- Brynjolfsson, E., Hu, Y., & Simester, D. (2011). Goodbye Pareto principle, hello long tail: The effect of search costs on the concentration of product sales. *Management Science*, 57(8), 1373-1386. <https://doi.org/10.1287/mnsc.1110.1371>
- Bucklin, R. E., & Sismeiro, C. (2009). Click here for Internet insight: Advances in clickstream data analysis in marketing. *Journal of Interactive Marketing*, 23(1), 35-48. <https://doi.org/10.1016/j.intmar.2008.10.004>
- He, C., Ke, S., & Zhang, X. (2022). A model of product line marketing. *Management Science*, 68(8), 6100-6115. <https://doi.org/10.1287/mnsc.2021.4193>
- Markóczy, L., Li Sun, S., Peng, M. W., Shi, W., & Ren, B. (2013). Social network contingency, symbolic management, and boundary stretching. *Strategic Management Journal*, 34(11), 1367-1387. <https://doi.org/10.1002/smj.2072>
- Moe, W. W., & Fader, P. S. (2004). Dynamic conversion behavior at e-commerce sites. *Management Science*, 50(3), 326-335. <https://doi.org/10.1287/mnsc.1040.0153>
- Park, Y., Bang, Y., & Ahn, J. H. (2020). How does the mobile channel reshape the sales distribution in E-commerce? *Information Systems Research*, 31(4), 1164-1182. <https://doi.org/10.1287/isre.2020.0937>
- Paruchuri, S. (2010). Intraorganizational networks, interorganizational networks, and the impact of central inventors: A longitudinal study of pharmaceutical firms. *Organization Science*, 21(1), 63-80. <https://doi.org/10.1287/orsc.1080.0414>

- Rappuoli, R., & Aderem, A. (2011). A 2020 vision for vaccines against HIV, tuberculosis and malaria. *Nature*, 473(7348), 463-469. <https://doi.org/10.1038/nature10124>
- Ravindran, K., Susarla, A., Mani, D., & Gurbaxani, V. (2015). Social capital and contract duration in buyer-supplier networks for information technology outsourcing. *Information Systems Research*, 26(2), 379-397. <https://doi.org/10.1287/isre.2015.0572>
- Ringel, D. M., & Skiera, B. (2016). Visualizing asymmetric competition among more than 1,000 products using big search data. *Marketing Science*, 35(3), 511-534. <https://doi.org/10.1287/mksc.2015.0950>
- Shriver, S. K., & Bollinger, B. (2022). Demand expansion and cannibalization effects from retail store entry: A structural analysis of multichannel demand. *Management Science*, 68(12), 8829-8856. <https://doi.org/10.1287/mnsc.2022.4308>
- Snijders, T. A. B., Van de Bunt, G. G., & Steglich, C. E. G. (2010). Introduction to stochastic actor-based models for network dynamics. *Social networks*, 32(1), 44-60. <https://doi.org/10.1016/j.socnet.2009.02.004>
- Snijders, T. A. B. (1996). Stochastic actor-oriented models for network change. *The Journal of Mathematical Sociology*, 21(1-2), 149-172. <https://doi.org/10.1080/0022250X.1996.9990178>
- Snijders, T. A. B. (2017). Stochastic actor-oriented models for network dynamics. *Annual Review of Statistics and Its Application*, 4(1), 343-363. <https://doi.org/10.1146/annurev-statistics-060116-054035>
- Steglich, C., Snijders, T. A. B., & Pearson, M. (2010). Dynamic networks and behavior: Separating selection from influence. *Sociological Methodology*, 40(1), 329-393. <https://doi.org/10.1111/j.1467-9531.2010.01225.x>
- Wang, H., Wei, Q., & Chen, G. (2013). From clicking to consideration: A business intelligence approach to estimating consumers' consideration probabilities. *Decision Support Systems*, 56, 397-405. <https://doi.org/10.1016/j.dss.2012.10.052>
- Wang, J. Q., Li, R., & Wu, H. Y. (2018). The evolution of online public opinion based on spatial autocorrelation. *Data Analysis and Knowledge Discovery*, 2(2), 64-73.
- Wu, J., Li, S. S., Zhou, L. S., Shi, L., & Chen, J. (2017). Research on dynamic evolution of users' user' s relationships network in online health community based on stochastic actor-oriented model. *Journal of the China Society for Scientific and Technical Information*, 36(2), 213-220.
- Zou, T., Zhou, B., & Jiang, B. (2020). Product-line design in the presence of consumers' anticipated regret. *Management Science*, 66(12), 5665-5682. <https://doi.org/10.1287/mnsc.2019.3506>
- Zuo, M., Angelopoulos, S., Liang, Z., & Ou, C. X. J. (2023). Blazing the trail: Considering browsing path dependence in online service response strategy. *Information Systems Frontiers*, 25(4), 1605-1619. <https://doi.org/10.1007/s10796-022-10311-3>
- Zuo, M., Angelopoulos, S., Ou, C. X. J., Liu, H., & Liang, Z. (2023). Optimization of dynamic product offerings on online marketplaces: A network theory perspective. *Journal of Management Information Systems*, 40(4), 1328-1357. <https://doi.org/10.1080/07421222.2023.2267314>
- Zuo, M., Liu, H., Zhu, H., & Gao, H. (2019). Dynamic property of consumer-based brand competitiveness (CBBC) in human interaction behavior. *Industrial Management & Data Systems*, 119(6), 1223-1241. <https://doi.org/10.1108/IMDS-09-2018-0403>
- Zuo, M., Ou, C. X. J., Liu, H., Liang, Z., & Angelopoulos, S. (2020). Dynamic competition identification through consumers' clickstream data. In *Academy of Management Proceedings*, (Vol. 2020, No. 1), p. 19916). <https://doi.org/10.5465/AMBPP.2020.19916abstract> Briarcliff Manor, NY 10510: *Academy of Management*.