Guest editorial: Predictive modeling in logistics and supply chain management research using partial least squares structural equation modeling

There are many types of empirical research objectives that researchers can pursue in business, economic and social science research. These can be divided into five categories: confirmatory, explanatory, exploratory, descriptive and predictive research (Hair *et al.*, 2019, 2022). In this respect, Hofstadter (1951, p. 339) claims, "explanation and prediction are the two commonly used functions of scientific knowledge." This is still true today. Although prediction and explanation appear to be opposing goals, they do not contradict each other. Explanatory modeling uses statistical models to test causal relationships, while predictive modeling is defined as "the process of applying a statistical model or [a] data mining algorithm to data for the purpose of predicting new or future observations" (Shmueli, 2010, p. 291). Explanations could provide a cognitive pathway to predictions by helping us conceptualize complex phenomena; predictions, on the other hand, serve to test and refine explanations (Douglas, 2009). Nevertheless, explanation plays a dominant role in social science research by answering the why question that explains the causal mechanisms. If researchers only focus on the explanation without considering the prediction, they compromise their ability to understand the explanation (Douglas, 2009).

In the logistics and supply chain management (LSCM) field, the explanatory modeling paradigm is often used to test theories. Currently, for instance, many LSCM researchers are interested in understanding LSCM's effects and benefits not only in their research field, but also in those of unprecedented technologies and innovations, such as artificial intelligence, blockchain, metaverse, robotics and robotic process automation. These technologies pave the way for supply chain management (SCM) 4.0 (Hofmann *et al.*, 2019), supply chain (SC) analytics (Lodemann *et al.*, 2022), operator 4.0 (Romero *et al.*, 2020), smart manufacturing (Kusiak, 2018), metaverse (Queiroz *et al.*, 2023) and logistics 4.0 developments (Winkelhaus and Grosse, 2020) toward the 4.0 revolution industry era. Simultaneously, however, SCs need to become more sustainable (Brockhaus *et al.*, 2016; Sarkis, 2020) and resilient to disruption (Wieland and Durach, 2021; Novak *et al.*, 2021). This also applies to technological innovations as well as to structural changes and organizational measures. Consequently, establishing and empirically testing causal hypotheses to explain such far-reaching changes are often common research procedures (e.g. Mathauer and Hofmann, 2019; Richter *et al.*, 2020). However, strongly focusing on explanations could lead to an increasing number of theories aimed at explaining a certain phenomenon of interest, while a predictive model helps restrict the possible explanations and provides a reliable basis for decision making (Douglas, 2009).

Scientific inquiry is specifically used to "facilitate prediction, intervention, control, or other forms of actions" (Longino, 2002, p. 124). Explanatory modeling does not predict model parameters for new observations (Hair and Sarstedt, 2019), but predictive modeling helps assess specific explanatory variables' predictive power and, therefore, their practical relevance. More specifically, predictive power depicts a model's ability to generate adequate predictions for new observations (Shmueli and Koppius, 2011). Further, predictive modeling allows

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researchers to uncover new relationships and mechanisms underlying complex patterns and to compare and assess alternative theories (Shmueli, 2010).

In this regard, the predominant LSCM research could be complemented by a greater emphasis on prediction enabling researchers to optimize their findings, which would, in turn, have an impact on scholars' and practitioners' decision-making (Guenther *et al.*, 2023). LSCM researchers often frame their managerial recommendations as prescriptive statements by following inherent prediction logic. LCSM, for example, invests in technology with practical value for employees, which creates high acceptance and, in turn, ensures positive job performance and work engagement. Predictive models could provide support for this kind of decision-making in business practice, as they allow the verification of recommendations for managerial activities' predictive capability (Chin *et al.*, 2020; Shmueli *et al.*, 2016). LSCM researchers should, therefore, go beyond testing hypothesized relationships embedded in a nomological network by not only assessing whether the model coefficients are significant in order to test whether a theory can accurately predict an outcome of interest (e.g. company performance, risk resilience, and technology effectiveness), but also by developing skills to predict new data outcomes (Stank *et al.*, 2019; Yawar and Seuring, 2017).

LSCM research is increasingly shifting from universalistic to more multifaceted models (e.g. Bubicz *et al.*, 2019; Yawar and Seuring, 2017) by replacing or extending overemphasized theories that offer explanations based on suboptimal models (Schorsch *et al.*, 2017). General theories and abstract constructs might only provide abstract explanations (Garver, 2019). More specifically, since SC actors' and decision-makers' behaviors often differ from those that theory predicts (Schorsch *et al.*, 2017), researchers need to develop better predictive models to complement explanatory models, thereby generating theoretical insights and practical implications. This should allow researchers and practitioners to understand complex LSCM phenomena better by being able to use predictive modeling to test their models' predictive power. An example is researchers aiming to better understand how technological developments improve and change the way people work in order to serve as technology for humans (e.g. Hofmann *et al.*, 2019; Queiroz *et al.*, 2023). Consequently, purely explanatory modeling is not sufficient. Predictive modeling must also be undertaken to scrutinize and refine, for instance, a theoretical explanation of human interaction with technology.

In order to achieve the balance between explanations and predictions, it is essential to examine a multivariate analysis technique, such as partial least squares structural equation modeling (PLS-SEM), which is positioned to perform these two crucial analytical functions (Wold, 1982; Jöreskog and Wold, 1982). This methodological approach differs from that of covariance-based SEM (CB-SEM) (Jöreskog, 1978; Rigdon, 1998; Diamantopoulos and Siguaw, 2006), which was created for confirmatory and explanatory purposes (see Chin *et al.*, 2020; Hwang *et al.*, 2020; Rigdon *et al.*, 2017). Ringle *et al.* (2023) provide general motives for using PLS-SEM in data articles, such as researchers preferring to apply PLS-SEM as a causal-predictive approach to SEM (Becker *et al.*, 2023; Chin *et al.*, 2020; Sarstedt *et al.*, 2022; Wold, 1982) when aiming (1) to predict key target constructs and to identify key driver constructs, as well as (2) to explore (and to extend) an existing structural theory. PLS-SEM is a composite-based SEM that maximizes the endogenous constructs' and indicators' explained variance (Hair *et al.*, 2022). According to Gregor (2006), this trait combines theory explanation and prediction, allowing for both prediction and the capacity to describe the connections between theoretical constructs. However, many PLS-SEM researchers have frequently emphasized that the coefficient of determination (R^2) was the predictive nature of their analyses. The notion behind R^2 evaluates the in-sample model fit of the endogenous constructs' composite scores by using the model estimates to predict the total sample's individual case values. Consequently, the R^2 value only evaluates a model's explanatory power, which does not evaluate the model's ability to predict the outcomes of new observations not considered during the initial model estimation process. To reiterate, it is problematic to focus on metrics that assess a model's explanatory power, because even the best predictive model could differ from a model intended to determine the best explanatory model or could suffer from overfitting (see also Sarstedt and Danks, 2022). In other words, a good model fit (i.e. R^2) designed from an explanatory context could perform poorly in terms of its out-of-sample predictive power (Shmueli, 2010), therefore, limiting its practical applicability.

Alternatively, researchers should utilize the new generation of prediction metrics, such as $\text{PLS}_{\text{predict}}$ (Shmueli *et al.*, 2016, 2019) and the cross-validated predictive ability test (CVPAT). Specifically, $\text{PLS}_{\text{predict}}$ applies a holdout sample approach by using k-fold cross-validation to calculate the case-level predictions at both an item and a construct level. The PLS predict metric's focus (i.e. Q^2_{predict}, RMSE: root mean square error; MAE: mean absolute error) is, therefore, to provide the ability to assess a single theoretical model's out-of-sample prediction in addition to its in-sample prediction. When interpreting $\text{PLS}_{\text{predict}}$ results, the focus should be on the model's key endogenous construct, rather than on the prediction errors of all the endogenous constructs (see Shmueli *et al.*, 2019; for details of the guidelines for interpreting the $\text{PLS}_{\text{predict}}$ results).

Similarly, Liengaard *et al.* (2021) introduced CVPAT for predictive model comparison as an improvement of the out-of-sample prediction assessment in PLS-SEM, which Sharma *et al.* (2022) developed further to test a model's predictive capabilities. This approach allows researchers to statistically compare a model with a naïve mean value benchmark and a more demanding linear model benchmark. In addition, this approach could be used to evaluate several pertinent target constructs simultaneously or a specific target construct in isolation. The approach determines whether the model under analysis makes significantly better predictions than the prediction benchmarks. Researchers could potentially use the CVPAT to confirm a model's predictive power in future LSCM applications, because it has advantages over PLS prediction. However, given this approach's novelty, we anticipate that it could take some time for researchers to become accustomed to this new structural model evaluation.

Overall, the applications of the prediction assessment procedures outlined in this editorial should increase confidence in LSCM researchers' findings. This would also be a substantial step in further improving prediction procedures for testing theoretical models (i.e. the direct effect, mediating effect or moderating effect) as well as for conclusions based on a PLS-SEM study's results.

Observations on the special issue articles

Interest in and the execution of LSCM research with the PLS-SEM method has increased substantially during the last 15 years. However, much of this research has attempted to explain and confirm the relationships between attitudinal and perceptual concepts, as well as occasionally behavioral opinions, instead of focusing on prediction, particularly out-of-sample predictions, which are useful for generalizing from a sample to the population. We believe the special issue papers are an excellent first effort to demonstrate the importance of adding out-of-sample prediction to LSCM researchers' toolbox, particularly when they are just starting to use the next generation of prediction techniques.

The first article is "Using PLS-SEM for assessing negative impact and cooperation as antecedents of gray market in FMCG supply chains: An analysis of Spanish wholesale distributors" by Fernando Gimeno-Arias and José Manuel Santos-Jaén. This article focuses on the negative impact and cooperation as antecedents of the gray market of fast-moving consumer goods (FMCG) supply chains. The study uses PLS-SEM to analyze the data collected from Spanish wholesale intermediaries of FMCG products. The results reveal that the damage caused by the negative impact on the official distributor's performance and the cooperation provided by the manufacturer have different effects. While the negative impact is shown to be a powerful antecedent of participation in the gray market, the effect of perceived manufacturer cooperation does not show strong results. Gimeno-Arias and Santos-Jaén (2023) suggest that manufacturers should keep their transactions in the gray market at low levels and cooperate with official distributors to ensure the official channel strategy's efficiency.

A second article by Yizhen Xu, Wynne Chin, Yide Liu, and Kai He is titled "Do institutional pressures promote green innovation? The effects of cross-functional coopetition in green supply chain management." Xu *et al.* (2023) explore the impact of institutional pressures when promoting green innovation on the implementation of green supply chain management (GSCM). The researchers conducted a survey of Chinese companies and analyzed coercive pressure, normative pressure and mimetic pressure's effects when using PLS-SEM. The research finds that all three pressures are essential when promoting green innovation, as well as normative and mimetic pressures having significant positive effects on cross-functional coopetition. Cross-functional coopetition is also identified as a necessary condition for green innovation to occur. The research expands the application of institutional theory and deepens the understanding of dynamic capability theory in analyzing cross-functional coopetition's mediating effects on institutional pressures and green innovation.

The third article is "Opening the black box of big data's sustainable value creation: The mediating role of supply chain management capabilities and circular economy practices" by Randy Riggs, José L. Roldán, Juan C. Real, and Carmen M. Felipe. This article analyzes the relationship between big data analytics capabilities (BDAC) and sustainable performance, as well as the mediating roles that supply chain management capabilities (SCMC) and circular economy practices (CEP) play. The study applies PLS-SEM for causal and predictive purposes and tests the serial mediator. The results indicate that BDAC influences sustainable performance indirectly through SCMC and CEP, rather than through a direct impact. The study by Riggs *et al.* (2023) provides empirical evidence of the relationship between IT business value, SC and sustainability and undertakes novel predictive analyses.

The fourth article in this issue is "Could information sharing predict fresh produce supply chain performance amid the COVID-19 pandemic? A social learning perspective" by Luluk Lusiantoro, Tria Putri Noviasari, Mahfud Sholihin and Wakhid Slamet Ciptono. This research aims to assess the effect of information sharing on the fresh produce supply chain's (FPSC's) performance during the coronavirus disease 2019 (COVID-19) pandemic. An online survey was conducted on 197 small fresh produce retailers in Indonesia and the data was analyzed by using PLS-SEM with SmartPLS 4 software. The results show that information sharing is positively associated with information quality and that the two constructs are not directly associated with FPSC performance. Cognitive and affective appraisals mediate information sharing's effect on FPSC performance, whereas affective appraisal mediates the effect of information quality on FPSC performance. This research by Lusiantoro *et al.* (2023) highlights the importance of social learning during the COVID-19 pandemic to improve FPSC performance.

The fifth study is "If you don't care, I will switch: Online retailers' behavior on third-party logistics services" by Abdul Hafaz Ngah, Ramayah Thurasamy and Heesup Han. This article investigates the factors influencing the satisfaction and switching intention of third-party logistics (3PL) services on online retailers in Malaysia. The study introduces a new model using the S-O-R model to predict online retailers' switching intention regarding 3PL providers. The study applies PLS-SEM to undertake its analysis. The results reveal that conflict handling affects satisfaction positively and that satisfaction has a negative relationship with online retailers' switching intention regarding 3PL. In addition, the study confirms that customer relationship management plays a moderating role in influencing the relationship between satisfaction and switching intention. This study by Ngah *et al.* (2023) offers insightful information for 3PL managers with regard to crafting their policies better to avoid their customers' switching behavior.

The sixth article is "Impact of fake news on firm performance during COVID-19: An assessment of moderated serial mediation using PLS-SEM by Eijaz Ahmed Khan, Maruf Hossan Chowdhury, Mohammad Alamgir Hossain, Abdullah M. Baabdullah, Mihalis Giannakis and Yogesh Dwivedi. This article discusses the impact of fake news on firm performance during the COVID-19 pandemic. The PLS-SEM results indicate that the impact of fake news on social media does not affect firm performance directly. However, supply chain disruption (SCD) and supply chain resilience (SCR) sequentially mediate the relationship between social media fake news and firm performance. In addition, higher levels of supply chain learning (SCL) strengthen the SCD–SCR relationship. Khan *et al.*'s (2023) study provides a new theoretical and managerial perspective to understand fake news' impact on firm performance in the context of crises such as COVID-19.

The seventh study in this issue is "In search of a suitable way to deploy Triple-A capabilities by assessing AAA models' competitive advantage predictive capacity" by Juan A. Marin-Garcia, Jose A.D. Machuca and Rafaela Alfalla-Luque. This article determines that leveraging the agility, adaptability and alignment's Triple-A SC capabilities is the best approach to enhance competitive advantage. The researchers evaluate the predictive abilities of different Triple-A SC models, taking each capability into consideration separately, in order to identify which model has the highest predictive capability for a competitive advantage. They use BIC, BIC-Akaike weights and $\mathrm{PLS}_{\mathrm{predict}}$ in a sample of 304 plants from various countries and industries. The research findings indicate that in both in-sample and out-of-sample, the direct relationship model (DRM) has a greater predictive capability for competitive advantage than the mediated relationship model (MRM) does. Consequently, the DRM is considered the benchmark for research and practice, while the Triple-A SC capabilities are viewed as independent levers for performance and competitive advantage. This study by Marin-Garcia *et al.* (2023) is the first to consider the use of Triple-A SC capabilities to improve performance and competitive advantage, while also focusing on predictive capability, which is crucial for decision making.

The last study by Ignacio Cepeda-Carrion, David Alarcon-Rubio, Carlos Correa-Rodriguez and Gabriel Cepeda-Carrion is titled "Managing customer experience dimensions in B2B express delivery services for better customer satisfaction: A PLS-SEM illustration." This article analyzes the relationship between customer experience and customer satisfaction in the express parcel industry in the business-to-business (B2B) context. The study investigates how basic service experience predicts moments of truth and focuses on results and peace of mind, which, in turn, lead to customer satisfaction. The authors collected data from 185 industrial customers in Spain and used PLS-SEM to analyze these. The research findings indicate that the four dimensions of customer experience form the foundation of express parcel companies' business success (i.e. customer satisfaction) in the B2B environment. Cepeda-Carrión *et al.* (2023) emphasize the importance of understanding customer needs by providing a unique experience beyond purely technical service delivery.

Final thoughts

As evidenced by this brief overview of the diverse articles in this special issue, the topic of prediction within the LSCM business field is a thriving and ongoing research effort. This is because most of these articles begin by positioning their objective of research based on causal prediction and subsequently use the $\mathrm{PLS}_{\mathrm{predict}}$ technique to generalize their findings. Kaplan (1964, p. 350) notes that "[i]f we can predict successfully on the basis of a certain explanation, we have a good reason, and perhaps the best sort of reason, to accept the explanation." One of our original goals for this special issue was to include papers that illustrate how the original PLS-SEM method's suggested advances are practically relevant for predicting LSCM phenomena. We believe you will agree that the articles in this special issue are bound to trigger substantial interest in advancing the next-generation prediction technique further by combining $PLS_{predict}$ and CVPAT techniques. We urged LSCM and other business field scholars to integrate both prediction techniques into their reporting (for proper guidelines, please refer to, for example, Sarstedt *et al.*, 2023; Guenther *et al.*, 2023).

In addition, we encourage LSCM researchers to keep abreast with new predictive capability assessments due to its importance for evaluating research findings' practical impact. There is currently an increasing focus on practical impact. This is likely to promote further improvement in out-of-sample prediction tests by combining Sharma *et al.*'s (2019, 2021) approach of utilizing information criteria (i.e. BIC: Bayesian information criterion and GM: Geweke-Meese criterion) in order to help researchers compare models' predictive capabilities. Sharma *et al.*'s (2022) improved CVPAT version was inspired by this predictive direction, which Liengaard *et al.* (2021) originally developed. It also allows researchers to test a theoretically established alternative model against the theoretically established original model. The results then show whether the alternative model has significantly greater predictive power than the original model.

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