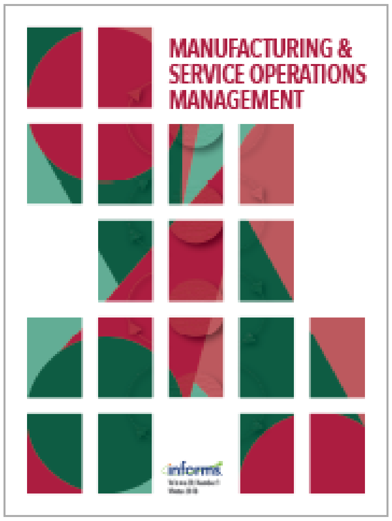

Manufacturing & Service Operations Management

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

MSOM Society Student Paper Competition: Abstracts of 2024 Winners

MANUFACTURING & SERVICE OPERATIONS MANAGEMENT
Vol. 27, No. 3, May–June 2025, pp. xviii–xx
https://pubsonline.informs.org/journal/msom
ISSN 1523-4614 (print), ISSN 1526-5498 (online)

MSOM Society Student Paper Competition: Abstracts of 2024 Winners

https://doi.org/10.1287/msom.2025.studentabs.v27.n3

Abstract. The journal is pleased to publish the abstracts of the four finalists of the 2024 Manufacturing and Service Operations Management Society's student paper competition. The 2024 prize committee was chaired by Vasiliki Kostami (HEC), Simone Marinesi (Wharton), and Fanyin Zheng (Imperial). The judges were Abhishek Deshmane, Agni Orfanoudaki, Alp Akcay, Alper Nakkas, Amrita Kundu, Antoine Desir, Anton Ovchinnikov, Anyan Qi, Ashish Kabra, Auyon Siddiq, Benjamin Legros, Bilal Gokpinar, Bin Hu, Bob Batt, Bora Keskin, Brent Moritz, Can Zhang, Chiara Farronato, Chloe Glaeser, Christopher Chen, Cuihong Li, Daniel Lin, David Drake, Dawson Kaaua, Ekaterina Astashkina, Elodie Adida, Emre Nadar, Ersin Korpeoglu, Esmaeil Keyvanshokooh, Fei Gao, Fernanda Bravo, George Chen, Georgina Hall, Gloria Urrea, Gonzalo Romero, Guillaume Roels, Guoming Lai, Heikki Peura, Hessam Bavafa, Ho-Yin Mak, Hummy Song, Huseyin Gurkan, Ioannis Bellos, Jean Pauphilet, Jiahua Wu, Jiankun Sun, Jiaru Bai, Jiayi Yu, Jing Wu, Jinglong Zhao, Joel Wooten, John Silberholz, Jonas Oddur Jonasson, Jose Guajardo, Julien Grand-Clement, Junyu Cao, Kaitlin Daniels, Lennart Baardman, Leon Valdes, Luyi Gui, Luyi Yang, Mazhar Arikan, Melvin Drent, Meng li, Mengzhenyu Zhang, Miao Bai, Mihalis Markakis, Mika Sumida, Ming Hu, Mirko Kremer, Mohamed Mostagir, Morvarid Rahmani, Mostafa Rezaei, Mumin Kurtulus, Nan Yang, Nazli Sonmez, Nektarios Oraiopoulos, Nikos Trichakis, Nil Karacaoglu, Nitin Bakshi, Nur Sunar, Olga Perdikaki, Onesun Steve Yoo, Ovunc Yilmaz, Ozge Sahin, Panos Markou, Pengyi Shi, Philip Zhang, Philipp Cornelius, Qiuping Yu, Rouba Ibrahim, Ruslan Momot, Ruth Beer, Ryan Cory-Wright, Saed Alizamir, Safak Yucel, Sajjad Najafi, Samantha Keppler, Samuel Burer, Sanjith Gopalakrishnan, Santiago Gallino, Scott Rodilitz, Sebastien Martin, Sheng Liu, Shouqiang Wang, Sidika Tunc Candogan, Sina Khorasani, So Yeon Chun, Somya Singhvi, Song-Hee Kim, Soo-Haeng Cho, Stefanus Jasin, Stephen Leider, Svenja Sommer, Tamer Boyaci, Thodoris Lykouris, Tian Chan, Tim Kraft, Tugce Martagan, Vahideh Manshadi, Vianney Perchet, Vishal Agrawal, Wanning Chen, Woonam Hwang, Xiaocheng Li, Xiaojia Guo, Xiaoshan Peng, Xiaoyang Long, Yangfang Helen Zhou, Yao Cui, Yehua Wei, Yi-Chun Akchen, Ying-Ju Chen, Yixin Iris Wang, Yuan-Mao Kao, Yuexing Li, Zhaohui Jiang, Zhaowei She, Zhe Liu, Zhen Lian, and Zumbul Atan.

The 2024 prize winners are as follows:

First Prize
Dynamic Matching with Post-Allocation Service and Its Application to Refugee Resettlement
Soonbong Lee, Yale School of Management

Second Prize
Signaling Competition in Two-Sided Markets
Yuri Resende Fonseca, Columbia Business School

Finalists (in alphabetical order according to the author's last name)
Optimizing Health Supply Chains with Decision-Aware Machine Learning
Tsai-Hsuan Chung, The Wharton School, University of Pennsylvania

Causal Message Passing: A Method for Experiments with Unknown and General Network Interference
Sadegh Shirani, Stanford Graduate School of Business

Dynamic Matching with Post-Allocation Service and Its Application to Refugee Resettlement

Soonbong Lee
Yale School of Management, soonbong.lee@yale.edu
Coauthors: Kirk Bansak, University of California, Berkeley; Vahideh Manshadi, Yale School of Management; Rad Niazadeh, Booth School of Business, University of Chicago; Elisabeth Paulson, Harvard Business School
Advisor: Vahideh Manshadi, Yale School of Management

Motivated by our collaboration with a major refugee resettlement agency in the United States, we study a dynamic matching problem where each new arrival (a refugee case) must be matched immediately and irrevocably to one of the static resources (a location with a fixed annual quota). In addition to consuming the static resource, each case requires post-allocation service from a server, such as a translator. Given the time-consuming nature of service, a server may not be available at a given time, thus we refer to it as a dynamic resource. Upon matching, the case will wait to avail service in a first-come-first-serve manner. Bursty matching to a location may result in undesirable congestion at its corresponding server. Consequently, the central planner (the agency) faces a dynamic matching problem with an objective that combines the matching reward (captured by pair-specific employment outcomes) with the cost for congestion for dynamic resources and over-allocation for the static ones. Motivated by the observed fluctuations in the composition of refugee pools across the years, we design algorithms that do not rely on distributional knowledge constructed based on past years' data. To that end, we develop learning-based algorithms that are asymptotically optimal in certain regimes, easy to interpret, and computationally fast. Our design is based on learning the dual variables of the underlying optimization problem; however, the main challenge lies in the time-varying nature of the dual variables associated with dynamic resources. To overcome this challenge, our theoretical development brings together techniques from Lyapunov analysis, adversarial online learning, and stochastic optimization. On the application side, when tested on real data from our partner agency, our method outperforms existing ones making it a viable candidate for replacing the current practice upon experimentation.

Signaling Competition in Two-Sided Markets

Yuri Resende Fonseca
Stanford University, yrf2001@stanford.edu
Advisors: Omar Besbes, Columbia University; Ilan Lobel, New York University; Fanyin Zheng, Imperial College London

We consider decentralized platforms facilitating many-to-many matches between two sides of a marketplace. In the absence of direct matching, inefficiency in market outcomes can easily arise. For instance, popular supply agents may garner many units from the demand side, while other supply units may not receive any match. A central question for the platform is how to manage congestion and improve market outcomes. We study the impact of a detail-free lever: the disclosure of information to agents on current competition levels. Disclosing competition reduces the perceived value of popular units, but, at the same time, it can help agents on the other side better elect across options. How large are such effects, and how do they affect overall market outcomes? We answer this question empirically. We partner with the largest service marketplace in Latin America, which sells nonexclusive labor market leads to workers. We propose a structural model which allows workers to internalize competition at the lead level and captures the equilibrium effect of such reaction to competition at the platform level. We estimate the model by leveraging agents' exogenous arrival times and a change in the platform's pricing policy. Using the estimated model, we conduct counterfactual analyses to study the impact of signaling competition on workers' lead purchasing decisions, the platform's revenue, and the expected number of matches. We find that signaling competition is a powerful lever for the platform to reduce congestion, redirect demand, and ultimately improve the expected number of matches for the markets we analyze.

Optimizing Health Supply Chains with Decision-Aware Machine Learning

Tsai-Hsuan Chung
The Wharton School, University of Pennsylvania, angelchg@wharton.upenn.edu
Coauthors: Hamsa Bastani, The Wharton School, University of Pennsylvania; Osbert Bastani, University of Pennsylvania; Francis Smart, Government of Sierra Leone - Ministry of Health and Sanitation; Lawrence Sandi and Jatu Abadulai, Government of Sierra Leone; Patrick Bayoh, Sierra Leone National Medical Supplies
Advisor: Hamsa Bastani, The Wharton School, University of Pennsylvania

A critical challenge in healthcare systems in Low- and Middle-Income Countries (LMICs) is the efficient and equitable allocation of scarce resources, particularly essential medicines. This problem is complicated by limited high-quality data, which restricts the applicability of traditional data-driven techniques. We propose a novel machine learning framework for essential medicines allocation, which leverages a combination of multitask learning and decision-aware learning to improve sample efficiency and ensure equitable allocation. In collaboration with the Sierra Leone national government, our framework has been deployed nationwide as a decision support tool to help reduce waste and improve essential medicines allocation. Our evaluation using synthetic difference-in-differences analysis demonstrates a 19% increase in medicine consumption, with no changes to the supply, improving access for approximately 3.7 million women and children under five. Through experimental validation, we demonstrate that our approach also significantly outperforms baseline approaches. Our work demonstrates the tangible impact of machine learning in optimizing high-stakes decisions in resource-constrained settings, improving efficiency while ensuring equity and cost-effectiveness.

Causal Message Passing: A Method for Experiments with Unknown and General Network Interference

Sadegh Shirani
Stanford Graduate School of Business, sshirani@stanford.edu
Coauthor and Advisor: Mohsen Bayati, Stanford Graduate School of Business

***Problem definition*:** Randomized experiments are a powerful methodology for evaluating decisions or interventions using data. However, their validity can be compromised by network interference, which occurs when the treatment of one unit affects not only its outcome but also the outcomes of connected units. This is common in social sciences or online marketplaces, leading to biases in traditional estimators. This study introduces a new framework to handle complex and unknown network interference, advancing beyond specialized models in existing literature. ***Methodology/results*:** Drawing inspiration from molecular vibration phenomena and insights from statistical physics, we introduce a new framework to address this problem. Our framework, termed causal message-passing, utilizes a high-dimensional approximate message-passing methodology to account for unit-specific interactions. We show that analyzing two one-dimensional dynamics suffices to detect the causal effect of an intervention, instead of investigating high-dimensional experimental data. This leads to a practical algorithm for estimating the total treatment effect, defined as the impact observed when all units are treated compared with when no units receive treatment. We demonstrate the effectiveness of this approach across five numerical scenarios, each with a distinct interference structure. ***Managerial implications*:** Our causal message-passing framework simplifies the detection of causal effects in complex networks, offering a robust alternative to traditional methods that require extensive assumptions about interference structures. This practical algorithm can significantly enhance the precision and reliability of treatment effect estimates in data-driven decision-making problems.