Zhiqi Zhang

CONTACT INFORMATION

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RESEARCH INTERESTS

Digital Platforms, Artificial Intelligence, Machine Learning, Causal Inference, Field Experiment, Structural Model

EDUCATION

Washington University in St. Louis

- Ph.D. in Supply Chain, Operations, and Technology 2021–Present
- Advisor: Dennis J. Zhang

Shanghai Jiao Tong University

- B.Eng. in Industrial Engineering 2016–2020

Yale University

- Summer Session Jul. 2017–Aug. 2018

PUBLICATIONS

1. Deep Learning Based Causal Inference for Large-Scale Combinatorial Experiments: Theory and Empirical Evidence, with Zikun Ye, Dennis Zhang, Heng Zhang, Renyu Zhang, *Forthcoming at* ***Management Science***.
   - Accepted at ACM Conference on Economics and Computation (EC'23)
   - Second Prize, CSAMSE Best Paper Award, 2023

WORKING PAPERS

1. Personalized Policy Learning through Discrete Experimentation: Theory and Empirical Evidence, with Zhiyu Zeng, Ruohan Zhan, Dennis Zhang. ***Job Market Paper***.
   - Winner of Buchan Prize Paper Competition, Olin Business School, 2025
2. The Impacts of Recommendations on Consumption and Creation on Online Content-Sharing Platforms, with Zhiyu Zeng, Tat Chan, Dennis Zhang, *major revision at* ***Management Science***.
3. Bias in Offline Retailing Experiment: Evidence and Solution, with Jiayi Zhang, Ruohan Zhan, Dennis Zhang, work in progress.

TEACHING EXPERIENCE

Guest Lecturer

- Stochastic Models for Production and Service Systems Spring 2024

Teaching Assistant

- Undergraduate Core
  - Data Analytics in Python Spring 2025
  - Operations Analytics Spring 2023
- Master Core
  - Data Analytics in Python Spring 2025
  - Operations Analytics Spring 2023
  - Operations Management Spring 2023, Fall 2022
- PhD Core:

- Dynamic Programming Fall 2024
- AI & Machine Learning for Business Applications Fall 2022, 23, 24

HONORS AND AWARDS

- Buchan Prize Paper Competition, Olin Business School 2025 2025
- Moog Scholar Award, Olin Business School 2025
- Second Prize, CSAMSE Best Paper Award 2023

PROFESSIONAL SERVICES

- Session Chair: 2024, 2025 INFORMS Annual Meeting
- Session Chair: 2024 POMS-HK Annual Meeting
- Reviewer: 2025 INFORMS workshop on Data Science, 2025 INFORMS BOM Best Working Paper Competition

CONFERENCE PRESENTATIONS

"Personalized Policy Learning through Discrete Experimentation: Theory and Empirical Evidence"

- POMS Annual Meeting, Atlanta, GA 2025
- POMS-HK International Conference, Hong Kong 2025
- INFORMS Annual Meeting, Seattle, WA 2024
- Conference on Digital Experimentation @ MIT, Cambridge, MA 2024
- MSOM Annual Meeting, Minneapolis, MN 2024
- POMS Annual Meeting, Minneapolis, MN 2024
- INFORMS Annual Meeting, Phoenix, AZ 2023

"Deep Learning Based Causal Inference for Large-Scale Combinatorial Experiments: Theory and Empirical Evidence"

- Workshop on Empirical Research in Operations Management, The Wharton School, Philadelphia, PA, 2023
- POMS Annual Meeting, Orlando, FL 2023
- INFORMS Annual Meeting, Indianapolis, IN 2022
- POMS Annual Meeting, Virtual Conference 2022

"The Impact of Recommendations on Consumption and Creation on Online Content-Sharing Platforms"

- POMS Annual Meeting, Orlando, FL 2023

INDUSTRY EXPERIENCE

- **Economist Research Intern**, Kwai.Inc 2020-2021
- **Consulting Project Lead**, Emerson (Spring 2025), Edward Jones (Spring 2024), Bunge (Fall 2023, Spring 2023), Express Scripts (Fall 2022)

SKILLS AND OTHER INFORMATION

Programming Languages: Python, R, SQL, C/C++, HTML, LaTeX
Language: English, Mandarin

ABSTRACT OF THE JOB MARKET PAPER

Personalized Policy Learning through Discrete Experimentation: Theory and Empirical Evidence

Randomized Controlled Trials (RCTs), or A/B testing, have become the gold standard for optimizing various operational policies on online platforms. However, RCTs on these platforms typically cover a limited number of discrete treatment levels, while the platforms increasingly face complex operational challenges involving optimizing continuous variables, such as pricing and incentive programs. The current industry practice involves discretizing these continuous decision variables into several treatment levels and selecting the optimal discrete treatment level. This approach, however, often leads to suboptimal decisions as it cannot accurately extrapolate performance for untested treatment levels and fails to account for heterogeneity in treatment effects across user characteristics. This study addresses these limitations by developing a theoretically solid and empirically verified framework to learn personalized continuous policies based on high-dimensional user characteristics, using observations from an RCT with only a discrete set of treatment levels. Specifically, we introduce a deep learning for policy targeting (DLPT) framework that includes both personalized policy value estimation and personalized policy learning. We prove that our policy value estimators are asymptotically unbiased and consistent, and the learned policy achieves a $\sqrt{n}$-regret bound. We empirically validate our methods in collaboration with a leading social media platform to optimize incentive levels for content creation. Results demonstrate that our DLPT framework significantly outperforms existing benchmarks, achieving substantial improvements in both evaluating the value of policies for each user group and identifying the optimal personalized policy.

Last updated: August 2025