

Research Methods in Work and Organizational Psychology: Towards an Integration Between Theory-driven and Data-driven Modeling

Young Keynote Speaker

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Preamble

- Work and Organizational Psychology (WOP) encompasses a wide range of research and applied areas, exploring the intersections between individuals, groups, organizations, jobs, and policies.
 - According to *Journal Citation Reports*, there are **114** scientific journals categorized under “PSYCHOLOGY, APPLIED” and **403** under “MANAGEMENT”
 - Some of you specialize in:
 - Leadership Studies... others may not
 - Individual Differences... others may not
 - Safety at Work... others may not
 - Occupational Health... others may not
 - Vocational Behaviors... others may not
 - Human Resources Management... others may not [...]
 - Despite these diverse specializations, we all dedicate significant time to **Research Methods**.

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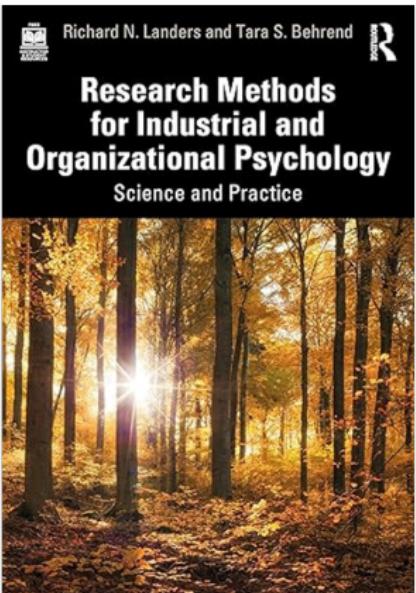
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Research Methods in WOP

- The adoption of advanced research methods and data analyses is becoming more and more important for conducting high-quality research in WOP
 - Whole journal: *Organizational Research Methods* (Academy of Management —Research Methods Division)
 - Book: Landers and Behrend (2024)
 - Growing number of books and special issues on HR Analytics (Bauer et al., 2024; Caughran, 2024; Edwards et al., 2024; Khan & Millner, 2023; McNulty, 2022; Starbuck, 2023)



Landers, R. N., & Behrend, T. S. (2024). *Research methods for industrial and organizational psychology: Science and practice*. Routledge.

Qualitative and Quantitative (well-known) Distinction

Two macro-areas in WOP Research Methods

- **Qualitative Research:** “[r]esearch focused on deep understanding and narrative description; typically involve collection of unstructured data and tends to be more exploratory” (Landers & Behrend, 2024, p. 443)
 - **Quantitative Research:** “[r]esearch focused on careful measurement and precision to capture information about constructs; typically relies on statistics” (Landers & Behrend, 2024, p. 443)

Philosophical (less-known...) Foundations

Ontology: What exists in the world that we can gain knowledge about?

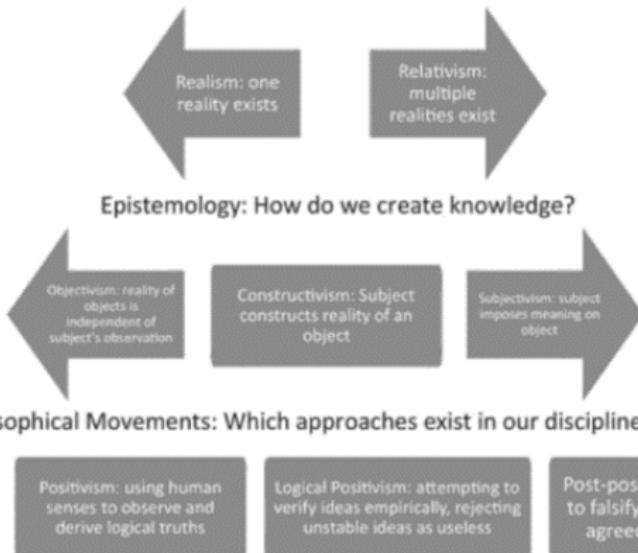


Figure 1.1 Ontology, epistemology, and philosophical movements relevant to I-O psychology.

Source: Landers and Behrend (2024, p. 5).

See also Chapter 6 in Braun and Clarke (2022) for a thorough discussion on philosophical foundations in empirical research

Epistemology in Quant Research

Theory-Driven vs Data-Driven Modeling

- **Theory-driven** modeling

- *Approach*: Hypothetico-deductive (from theory to data)
- *Label*: Confirmatory
- *Aim*: Explanation

- **Data-driven** modeling

- *Approach*: Inductive (from data to insights)
- *Label*: Exploratory
- *Aim*: Prediction

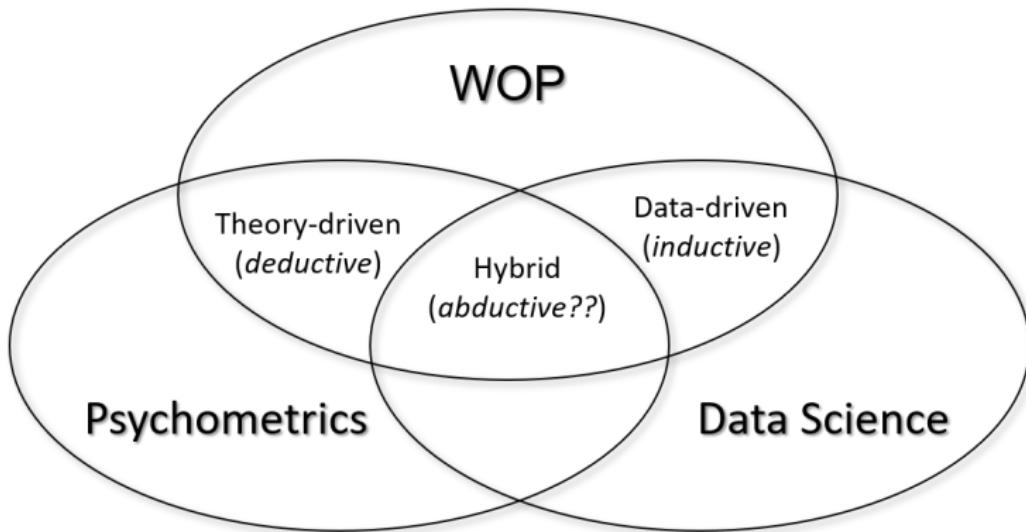
- In **Statistics**, this debate has at least two decades (Breiman, 2001; Shmueli, 2010)
- In **Psychology**, it's rather new (Jacobucci, 2022; Paxton & Griffiths, 2017; Yarkoni & Westfall, 2017)
- In **WOP and Management** it's even newer (Leavitt et al., 2021; Woo et al., in press)

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Towards a paradigm shift?



Integration between WOP and two methodological areas

Intro

Theory-driven modeling in WOP

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Theory in WOP

“Management and organizational scholars have defined theory in similar ways over the past several decades. For example, Davis (1971); Bacharach (1989); Whetten (1989); Weick(1995); Sutton and Staw (1995); Alvesson and Sandberg (2011); Ragins (2012); Bettis, Gambardella, Helfat, and Mitchell (2014); Sudaby (2014); Cornelissen (2017); and van Nordenflicht (2023), among others, focus on concepts, relationships, assumptions, boundary conditions, consistency, parsimony, and falsifiability.

Drawing from these articles and other salient sources, we define theory as an explanation of the relationships between constructs or concepts that show how and why a phenomenon occurs.”

(Thatcher et al., 2024, p. 1183-1184)

Hypothesis in WOP

*“Many investigations go beyond raising questions by stating specific theoretical hunches, or hypotheses, about the outcomes of a study. **A hypothesis is the researcher’s best guess about what the results of a study will be.** Rather than merely raising the question, the hypothesis is a theoretical answer.*

Thus, one might hypothesize that ‘People who are well paid will like their jobs better than people who are not.’

or

‘People who are fairly paid will like their jobs more than people who are not.’

The hypothesis is a statement of the results that the researcher expects to find. Research studies are conducted to confirm hypotheses. In other words, do the results come out the way they were predicted?”

(Spector, 2017, p. 25)

Tell me how important theory is in WOP without telling me how important theory is in WOP...

Original Manuscript

Organizational
Psychology
Review



It's the Theory, Stupid

Organizational Psychology Review
1-20

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 SAGE

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Matthew A. Cronin 

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Abstract

To the complex question of “What is the number one issue on which we should focus as producers, evaluators, and consumers of research?” our simple and blunt answer is: *It's the theory, stupid*. Accordingly, we offer guidance on how to produce, test, and use theory by answering the following questions: (1) Why is theory so critical and for whom? (2) What does a good theory look like? (3) What does it mean to have too much or too many theories? (4) When don't we need a theory? (5) How does falsification work with theory? and (6) Is good theory compatible with current publication pressures? Our answers are useful to current and future scholars and journal editors and reviewers, as well as consumers of research including other researchers, organization decision makers, and policy makers, and other stakeholders in the theory production and testing process including deans and other university administrators.

Source: Aguinis and Cronin (in press)

Why theory is so important in WOP?

We need a thorough knowledge of WOP phenomena to

1. Measure variables that are not directly measurable (i.e., constructs)
2. Connect constructs to unravel complexities in their relationship

In this scenario, two areas of Psychometrics are essential for translating, testing, validating, and expanding WOP theories into empirical findings.

1. Psychological Assessment/Measurement (e.g., operationalization process, reliability, validity) (e.g., Cheung et al., 2024)
2. Data Analytic Techniques (e.g., G(z)LM, mediation/moderation, multilevel modeling, Structural Equation Modeling, person-centered approaches) (e.g., González-Romá & Hernández, 2023; Morin et al., 2018)

Substantive-Methodological Synergy

- Originally developed in **Psychometrics** (e.g., Borsboom, 2006) to enhance the exchange between substantive psychological areas and psychometric methods
- Now also widely adopted in WOP, as outlined by Hofmans et al. (2021) in a *I-O Psych* paper titled “*The baby and the bathwater: The need for substantive–methodological synergy*”. Main points:
 - The importance of methodological fit
 - Many phenomena in I-O psychology are multidetermined
 - Much of our data have a nested data structure
 - Psychological phenomena are usually dynamic
 - The questionable assumption of population homogeneity
 - Many theories, even simple in appearance, cannot be empirically tested without complex data analyses
 - The need for latent variable models
 - Random measurement error
 - Disentangling distinct sources of variance
 - Improved techniques for testing moderation

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Operationalization process in WOP

What we do when we operationalize a construct in WOP?

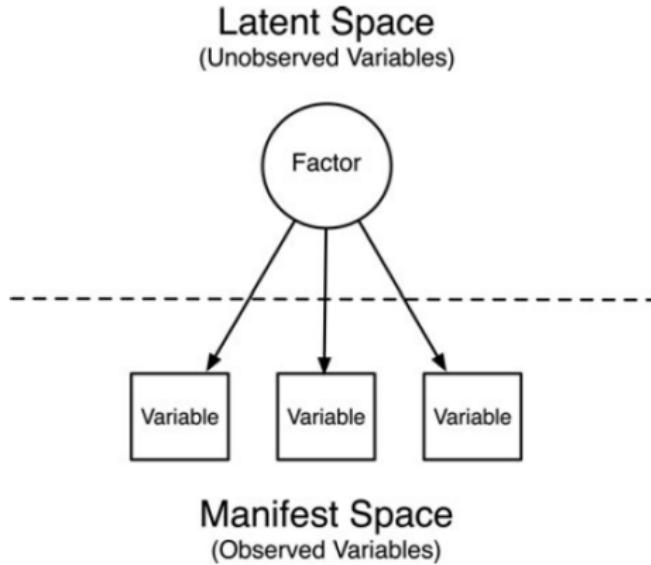
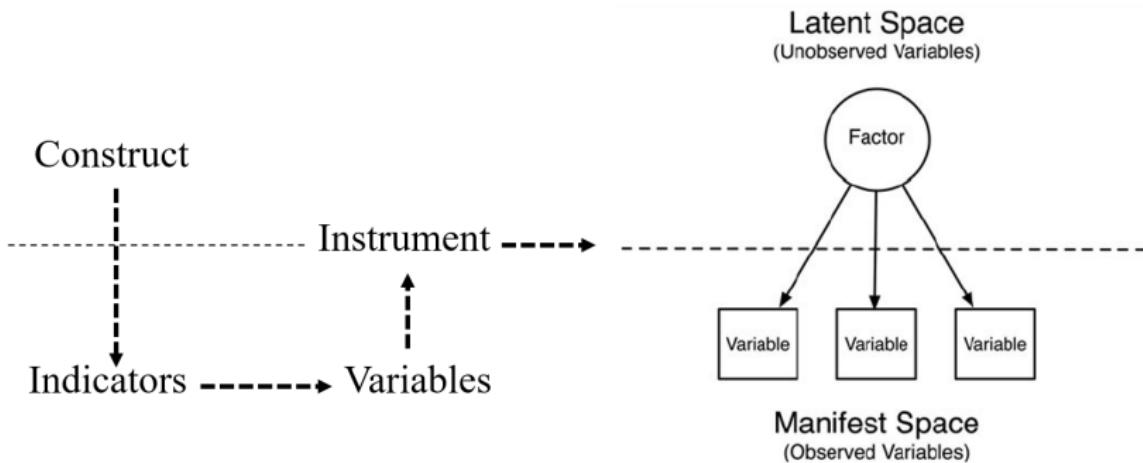


Figure 6. Factor loadings (arrows)—bridges between manifest and latent space.

Source: Nesselroade and Molenaar (2016, p. 404)

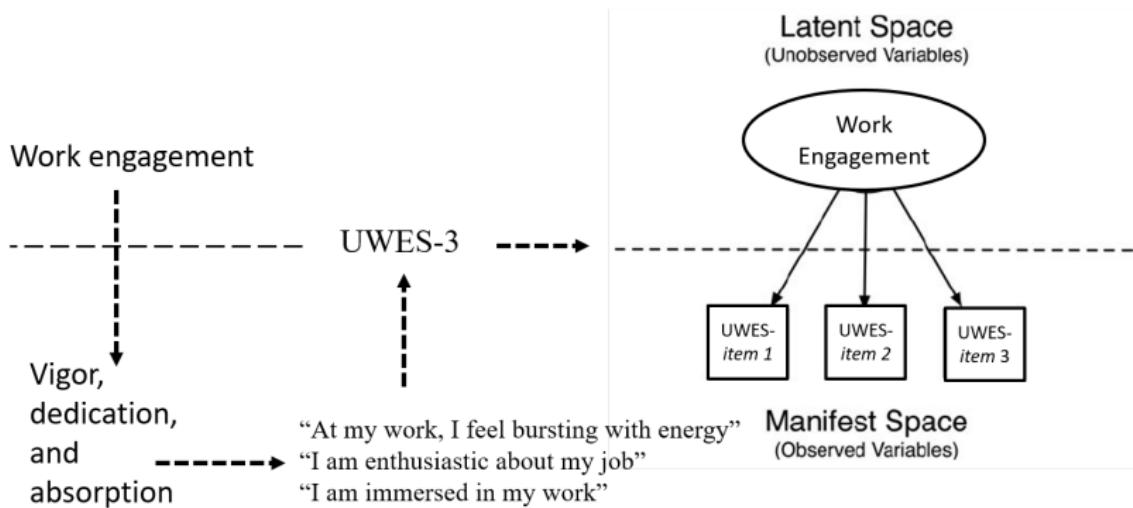
Operationalization process in WOP

What we do when we operationalize a construct in WOP?



Operationalization process in WOP

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Source of UWES-3: Schaufeli et al. (2017)

Operationalization process in WOP

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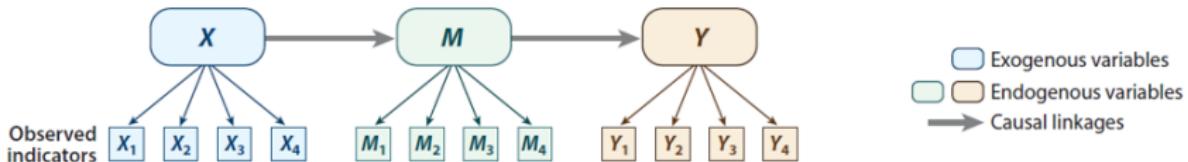
Validity in WOP:

- Substantive Validity
 - Face Validity (Allen et al., 2023)
 - Content Validity (Colquitt et al., 2019; Rossiter, 2008)
- Structural (Internal) Validity
 - Reliability (Cortina et al., 2020)
 - Measurement Invariance (Somaraju et al., 2022)
- External Validity
 - Construct/Nomological/Criterion Validity (e.g., Lambert & Newman, 2023)
 - Convergent Validity (Cheung et al., 2024)
 - Discriminant Validity (Cheung et al., 2024; Rönkkö & Cho, 2022)

Structural relationships among WOP constructs

What we do when we connect constructs in WOP?

- Test theory against data using Structural Equation Modeling
- Theory guides the way to which we specify a certain degree of misfit ($\Sigma(\Theta)$) in original data (Σ)
- Will data support theory, i.e. will $\Sigma = \Sigma(\Theta)$? (Bollen, 1989)



Source: Zyphur et al. (2023, p. 497)

Structural relationships among WOP constructs

What we do when we connect constructs in WOP?

The pivotal contribution of Longitudinal SEM

- Mostly based on *Granger causality* from econometrics (Granger, 1969)
- Improved test of mediation hypotheses (Aguinis et al., 2017)
- Track and link mean-level change, autoregression, and various sources of variances (trait, state, state-residual, uniqueness, etc.) of WOP constructs (e.g., Zhou et al., 2021)

Structural relationships among WOP constructs

What we do when we connect constructs in WOP?

The pivotal contribution of Longitudinal SEM

Some substantive-methodological contributions:

- Global self-esteem at work is not as stable as we thought ...
 - Reject the rigid separation between “state-constructs” and “trait-constructs”
 - Rather, focus on the trait and state components of each WOP construct (Perinelli & Alessandri, 2020)
- Global self-esteem at work is not only a predictor, as we thought ...
 - Findings based on the Sociometer Theory support the notion that social environment at work may affect workers' self-esteem levels (Perinelli, Alessandri, Cepale & Fraccaroli, 2022)
- Personality traits are not as stable as we thought ...
 - Instead, adaptability of traits may increase levels of organizational socialization and identification (Alessandri, Perinelli, Robins, Vecchione, & Filosa, 2020)

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Theory-driven Modeling in WOP

Conclusion

All the research methods and approaches discussed so far are (and should be treated as) **DEDUCTIVE**, and thus confirmatory and explanatory

Advantages

- Ability to test theories against data, from operationalization to structural relationships
- Ability to disentangle various sources of variance
- Ability to face with complex multivariate issues

Disadvantages

- Many parameters... but few constructs: A 3-wave model with only 3 constructs may require the estimation of more than 150 parameters.
- Difficulties in perfectly fit theory with data and vice-versa: What about unexpected findings? What about complex (hidden) non-linearities? What about the effect of other not-controlled variables?
- Over-optimistic estimates of explained variance: How well my model fit on future (unseen) data?
- It is difficult to merge Qualitative Research Methods into a single pipeline: Mixed-method designs often present qualitative and quantitative methods separately.

Intro

Theory-driven modeling in WOP

Data-driven modeling in WOP

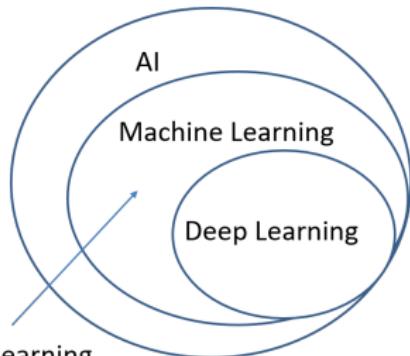
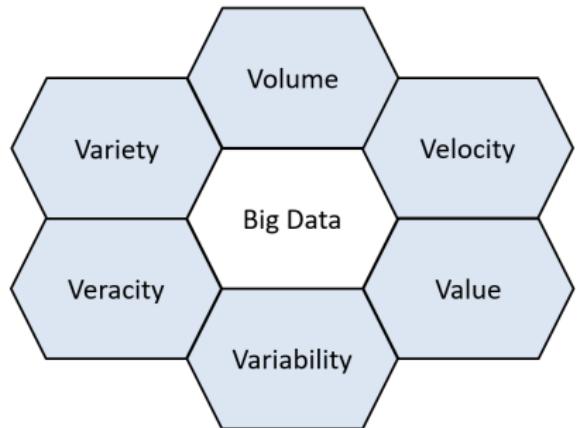
Towards an integration

Data-driven modeling

- Data-driven models belong to the “Algorithmic Modeling Culture”
- Mid-1980s: Neural nets and decision trees became available
- Mainly developed by computer scientists, physicists, and engineers (plus a few aging statisticians)
- Complex **prediction problems** where it was obvious that classical data models were not applicable (e.g., speech recognition, image recognition, nonlinear time series prediction, handwriting recognition, prediction in financial markets)

(Breiman, 2001, p. 205)

“Mainstream” Data-Driven Concepts



Shallow Learning

- Supervised
 - Regression
 - Classification
- Unsupervised
 - Dimension Reduction
 - Clustering

“Less-known” Data-Driven Concepts

Transformer

New deep learning architecture at the basis of the latest advancements in Large Language Models (e.g., GPT)

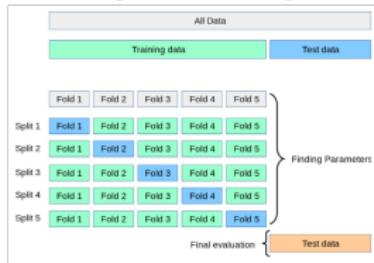
Attention is all you need

A Vaswani, N Shazeer, N Parmar, ... - Advances in neural ... , 2017 - proceedings.neurips.cc
... to attend to all positions in the decoder up to and including that position. We need to prevent ...
... We implement this inside of scaled dot-product attention by masking out (setting to $-\infty$) ...
★ Salva 99 Cita Citato da 126159 Articoli correlati Tutte e 91 le versioni 80

As of Aug 8, 2024

Cross-validation

https://scikit-learn.org/stable/modules/cross_validation.html



Regularization and Optimization

Loss function for Elastic Net (Rhys, 2020, p. 262)

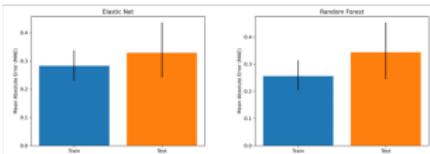
$$\text{loss function}_{\text{elastic}} = \sum_{i=1}^n (y_i - \hat{y}_i) + \lambda \left((1 - \alpha) \sum_{j=1}^p \beta_j^2 + \alpha \sum_{j=1}^p |\beta_j| \right) \quad \text{Equation 11.7}$$

Hyperparameter Tuning (Optimization) for Elastic Net in Python

```
# Parameters
elastic_r_parameter = {
    'alpha': [0.01, 0.025, 0.035, 0.04, 0.045, 0.05, 0.055, 0.06, 0.07, 0.1, 0.15, 0.2, 0.3, 0.4, 0.5, 0.6, 0.8, 1.0, 5.0, 10.0, 25.0, 50.0, 75.0, 100.0],
    'l1_ratio': [0.25, 0.50, 0.60, 0.70, 0.75, 0.80, 0.85, 1] # l1_ratio = 1 -> LASSO, l1_ratio = 0 -> Ridge
}
```

Overfitting

(Perinelli, Stella, Bizzego, Pisanu, & Fraccaroli, under review)



Data-driven Modeling in WOP

- The first milestones can probably be mapped in a *SIOP Organizational Frontiers Series* book (Tonidandel et al., 2016) and in an *ORM* special issue (Tonidandel et al., 2018)
- Since then:
 - 2 special issues on *Personnel Psychology* (Campion & Campion, 2023; Woo et al., in press)
 - 1 review on the *Annual Review of Org Psych and Org Behav* (Oswald et al., 2020)
 - Several articles on different topics, such as **leadership** (Tonidandel et al., 2022), **job analysis** (Putka et al., 2023), **turnover/performance** (Sajjadi et al., 2019), **work engagement** (van Roekel et al., 2024), **talent management systems** (Gonzalez et al., 2019), **safety outcomes** (Kumar & Burns, 2024), **personnel selection** (Koenig et al., 2023; Landers et al., 2023), **tutorial/best practices** (Putka et al., 2018; Sheetal et al., 2023), **Automatic Item Generation** (AIG) (Lee et al., 2023)

Data-driven Modeling in WOP

Epistemological Considerations

* *Academy of Management Review*
2021, Vol. 46, No. 4, 750–777.
<https://doi.org/10.5465/amr.2019.0247>

HOST IN THE MACHINE: ON ORGANIZATIONAL THEORY IN THE AGE OF MACHINE LEARNING

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Oregon State University

KIRA SCHABRAM
University of Washington

PRASHANTH HARIHARAN
Indian School of Business

CHRISTOPHER M. BARNES
University of Washington

With rapid advancements in machine learning, we consider the epistemological opportunities presented by this novel tool for promoting organizational theory. Our paper unfolds in three sections. We begin with an overview of the three forms of machine learning (supervised, reinforcement, and unsupervised), translating these onto our common modes of research (deductive, abductive, inductive, respectively). Next, we present frank critiques of machine learning applications for science, as well as of the state of organizational scholarship writ large, highlighting contemporary challenges in both domains. We do so to make the case that machine learning and theory are not in competition but have the potential to play complementary roles in moving our field beyond siloed domains and incremental theory. Our final section speaks to this synergy. We propose that machine learning can act as a tool to test and prune midrange theory, and as a catalyst to expand the explanatory spectrum that theory can inhabit. Specifically, we outline how machine learning can support *local* but perishable theory targeting pragmatic problems in the here and now, and *grand* theory that is sufficiently bold and generalizable across contexts and time to serve the social-functional purposes of inspiring and facilitating long-term epistemological progress across domains.

Source: Leavitt et al. (2021)

Data-driven Modeling in WOP

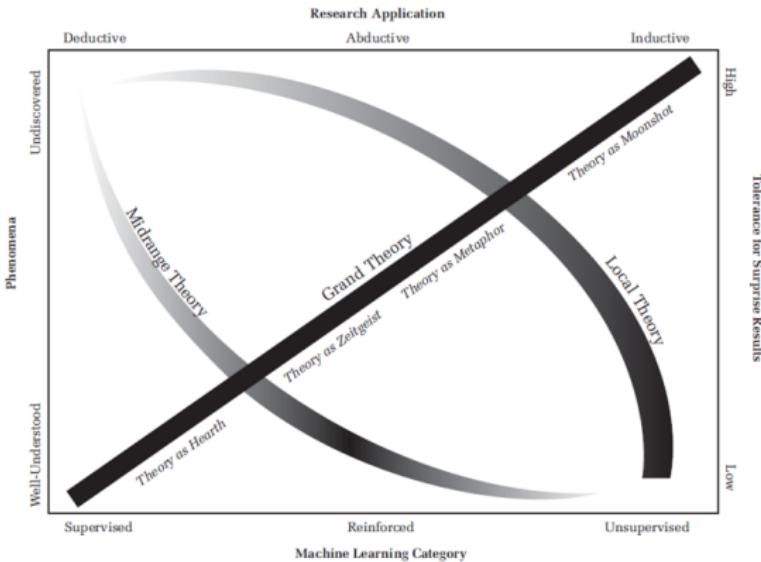
Epistemological Considerations

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Academy of Management Review

October

FIGURE 1
Mapping Machine Learning Applications onto the Explanatory Spectrum of Organizational Theory



Notes: Though we see the potential for synergy across the explanatory spectrum, we suggest that the most readily exploitable collaborations between ML and theory occur in the darkest parts of the curve. We outline these opportunities in the section entitled "The power of ML application for extending theory's explanatory spectrum."

Source: Leavitt et al. (2021)

Data-driven Modeling in WOP

Epistemological Considerations

- **Midrange Theory:** Explains specific phenomena with broader scope; detailed, applicable in various contexts. Dominates organizational science; Further reinforcement of well-established theories, instead of challenging already influential theories. Litany of constructs, models and theories that remain disconnected from one another.
- **Local Theory:** Targeting urgent, pragmatic problems in the here and now.
- **Grand Theory:** Sufficiently expansive, bold, and generalizable across contexts and time to serve the discrete social-functional purposes of organizing and inspiring.
- **Theory as Hearth:** Central point of cohesion and stability; creates community, stable foundation.
- **Theory as Zeitgeist:** Reflects ideas of a specific period ("spirit of the time"); culturally influenced, can become obsolete.
- **Theory as Metaphor:** Uses metaphors to explain phenomena; facilitates understanding, inspires new thinking.
- **Theory as Moonshot:** Long-term, audacious goals that require new approaches to problem-solving.

From Theory Proliferation to Theory Integration

Inductive Approach for Integrating Performance Theories

- Do you know how many theories of Performance (Firm and Individual) we have?

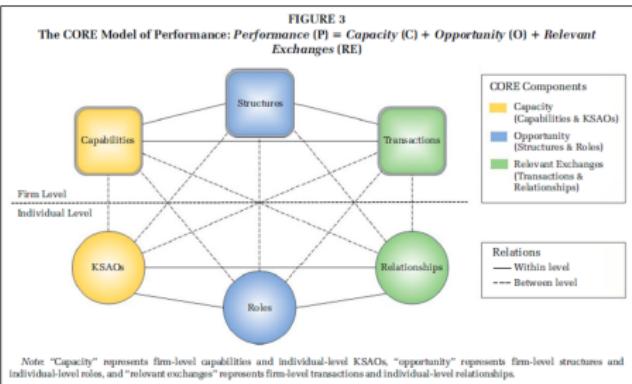
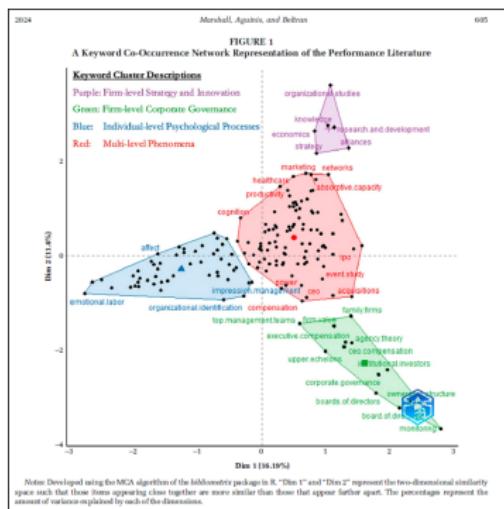
From Theory Proliferation to Theory Integration

Inductive Approach for Integrating Performance Theories

- Do you know how many theories of Performance (Firm and Individual) we have?
- According to Marshall, Aguinis, & Beltran (2024), in organizational science there are **239 theories** about firm and individual performance (see also Aguinis et al., 2024)

From Theory Proliferation to Theory Integration

Inductive Approach for Integrating Performance Theories



From 239 theories to 4 keyword co-occurrence clusters to 6 isomorphic meta-theoretical constructs.

Source: Marshall et al. (2024, p. 605 and p. 610)

Intro

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Data-driven modeling in WOP

Towards an integration

Do we need to integrate Theory-driven and Data-driven modeling in WOP Quantitative Research?

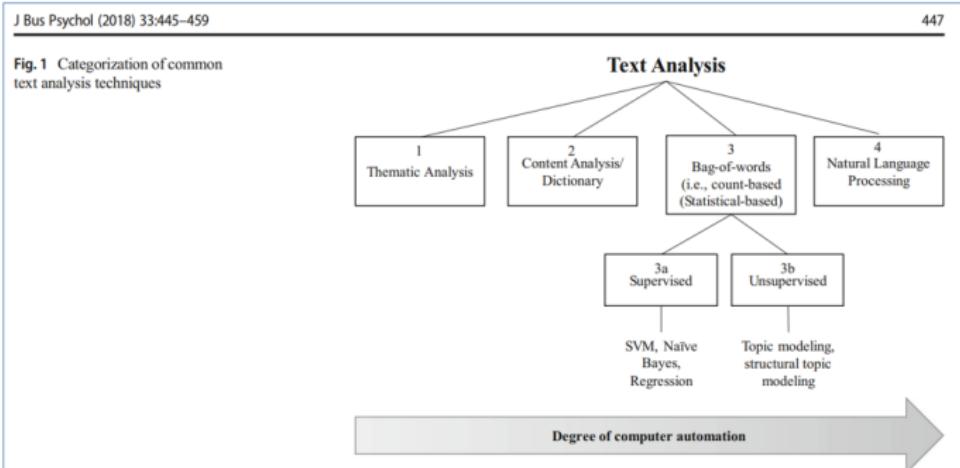
Some reasons

- It allows a better use of abductive reasoning, even in quantitative research methods:
 - Theories are reinforced, pruned, or merged; “identifying conclusions that synthesize competing or previously disconnected theoretical findings or perspectives” (Jacobucci et al., 2023, p. 19).
 - From data-driven to theory-driven models: Identifying robust empirical regularities and explaining them by abductively inferring underlying causal mechanisms (Haig, 2020).

Do we need to integrate Theory-driven and Data-driven modeling in WOP Quantitative Research?

Some reasons

- Better integration between qual and quant research (e.g., in analyzing textual data; Banks et al., 2018) and open the way to new assessment methods based on semantic/syntactic associations (Stanghellini et al., 2024)



Source: Banks et al. (2018, p. 447)

The Rise of Hybrid Methodological Techniques

Some examples

- Hybrid latent-variable machine-learning techniques, such as regularized SEM and SEM forests (Brandmaier & Jacobucci, 2023; Jacobucci et al., 2023)
- Exploratory Mediation Analysis (Serang et al., 2017)
- Deductive Data Mining (Hong et al., 2020)

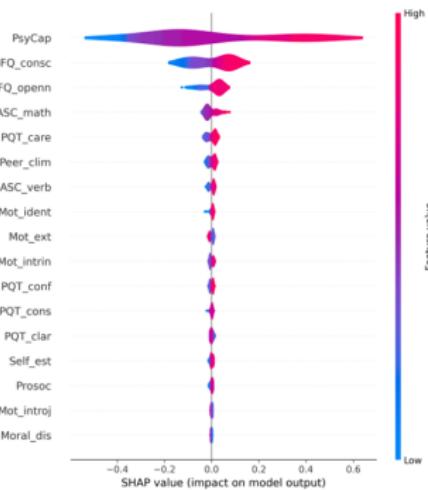
A Note on Explainable Artificial Intelligence (XAI)

Beyond Black Boxes: Making Machine Learning Interpretable

- Since 2017, the increasing development of techniques such as SHapley Additive exPlanations (**SHAP**) values, Partial Dependence Plots (**PDP**), and Accumulated Local Effects (**ALE**) Plots, has made the interpretation of ML results more interpretable (Molnar, 2022)
- Application in WOP: Nonlinearity in personality–job performance relations (Song et al., in press)

PSYCHOLOGICAL CAPITAL PREDICTORS

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Figure 7
SHAP Scores for Random Forests

Lagged predictors of PsyCap levels at T2
(paper under review)

Conclusion

Removing Barriers

- Drawing from the work by Paxton and Griffiths (2017), we can outline **three gaps** that prevent the use and acceptance of these new sources of data and data-analyses:
 - IMAGINATION GAP: the inability of researchers to see themselves, their research area, and their specific research question under (quantitative) inductive methods
 - CULTURE GAP: lack of acceptance of these approaches
 - SKILLS GAP: new tools, methods, and analyses to learn (König et al., 2020; Landers et al., 2019)
- In sum, many of the concerns can be overcome by recognizing two types of problems:
 - EPISTEMOLOGICAL: Clearly specify the epistemological position of both the research question and the data to be analyzed.
 - TECHNICAL: Enhance technical skills in programming languages (e.g., R and Python) and develop proficiency in novel data analytic strategies (e.g., XAI, NLP, etc.)

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Conclusion

The Future I See

- The role of Subject Matter Experts (SMEs) remains pivotal, as the validation of these approaches is and will continue to be essential (Woo et al., *in press*).
- Increased convergence and exchange between Quant and Qual methods (see Bliese et al., 2024).
- Greater emphasis on formalizing (quantitative) theories from computational and mathematical perspectives (Bliese et al., 2024; Grand et al., *in press*; van Dongen et al., *in press*). E.g., is the JD-R theory robust enough for predictive approaches?
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Thanks for your attention

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