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

Young Keynote Speaker

Enrico Perinelli

Department of Psychology and Cognitive Science
University of Trento

September 4, 2024

UNIVERSITÀ DI TRENTO
Dipartimento di Psicologia e Scienze Cognitive

Associazione Italiana di Psicologia

Immaginazione organizzativa, ricerca e azione trasformativa. Passato, presente e futuro delle pratiche di psicologia del lavoro e delle organizzazioni
XX Congresso Nazionale della Sezione di Psicologia per le Organizzazioni

Bergamo, 4-5-6 Settembre 2024

Table of Contents

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**.

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**.

Preamble

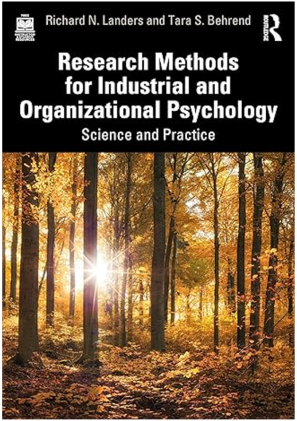
- Work and Organizational Psychology (WOP) encompasses a wide range of research and applied areas, exploring the intersections between individuals, groups, organizations, jobs, and policies.
- According to *Journal Citation Reports*, there are **114** scientific journals categorized under "PSYCHOLOGY, 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**.

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**.

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; Caughlin, 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

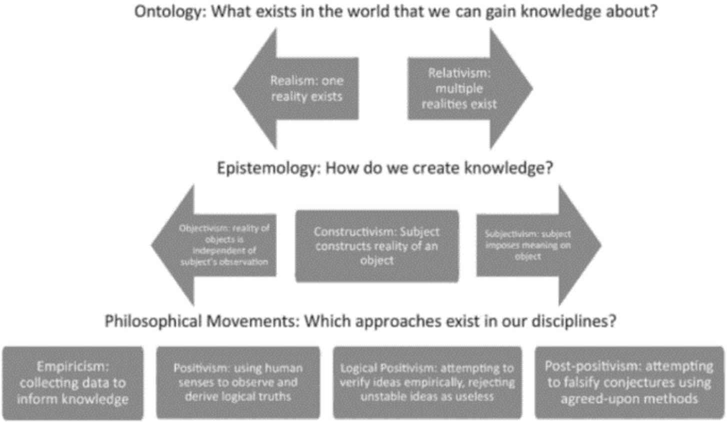


Figure 1.1 Ontology, epistemology, and philosophical movements relevant to I-O psychology.

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

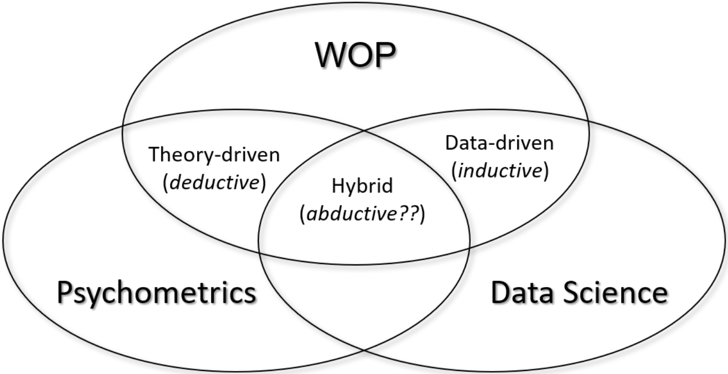
- **Theory-driven** modeling
  - *Approach:* Hypothetico-deductive (from theory to data)
  - *Label:* Confirmatory
  - *Aim:* Explanation
- **Data-driven** modeling
  - *Approach:* Inductive (from data to insights)
  - *Label:* Exploratory
  - *Aim:* Prediction
- In **Statistics**, this debate has at 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)

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)

Towards a paradigm shift?



Integration between WOP and two methodological areas

Intro

Theory-driven modeling in WOP

Data-driven modeling in WOP

Towards an integration

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); Suddaby (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

Organizational Psychology Review
1–20

DOI: 10.1177/20413866221080629
journals.sagepub.com/home/opr
SAGE

It's the Theory, Stupid

Herman Aguinis
Department of Management, The George Washington University

Matthew A. Cronin
Department of Management, George Mason University

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

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

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

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

Operationalization process in WOP

What we do when we operationalize a construct in WOP?

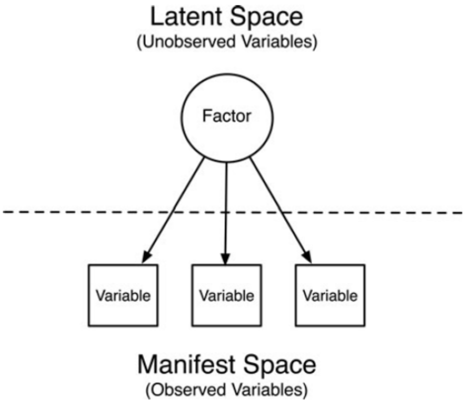
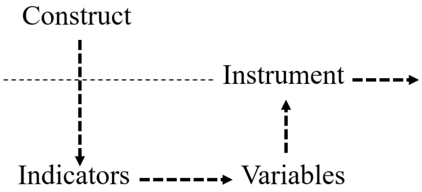


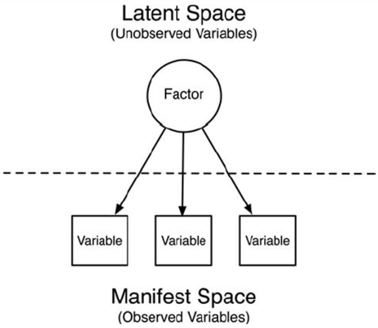
Figure 6. Factor loadings (arrows)—bridges between manifest and latent space.

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

Operationalization process in WOP

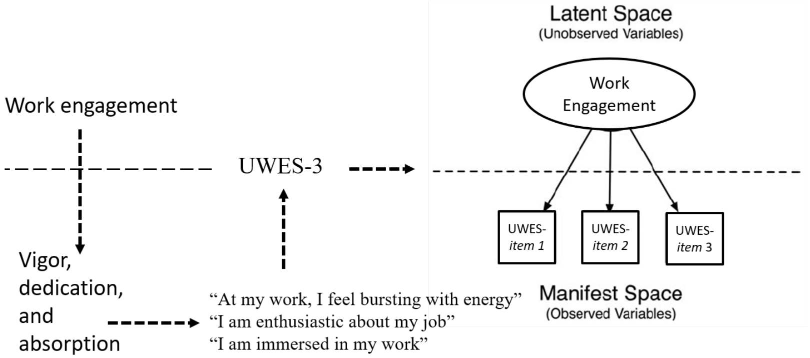
What we do when we operationalize a construct in WOP?





Operationalization process in WOP

What we do when we operationalize a construct in WOP?



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

Operationalization process in WOP

What we do when we operationalize a construct in WOP?

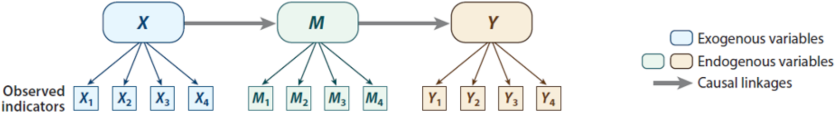
Validity in WOP:

- 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 ($\boldsymbol{\Sigma}(\boldsymbol{\Theta})$) in original data ($\boldsymbol{\Sigma}$)
- Will data support theory, i.e. will $\boldsymbol{\Sigma} = \boldsymbol{\Sigma}(\boldsymbol{\Theta})$?(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)

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)

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)

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

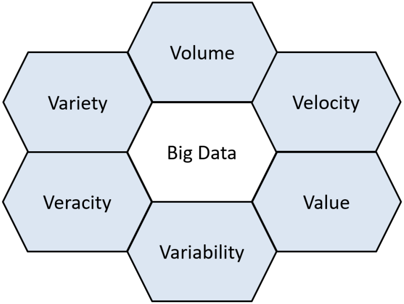
Towards an integration

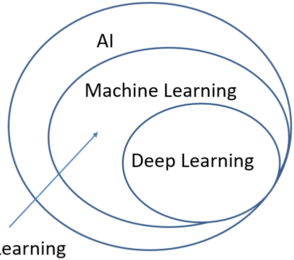
Data-driven modeling

- 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

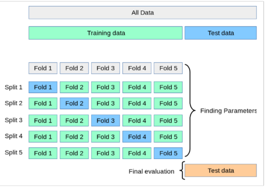
New deep learning architecture at the basis of the latest advancements in Large Language Models (e.g., GPT)

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 −∞) …
☆ Salva ፵ Cita Citato da 128159 Articoli correlati Tutte e 91 le versioni

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)

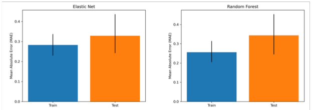
$$\text{loss function}_{\text{elastic}} = \sum_{i=1}^{n}(y_i - \hat{y}_i) + \lambda\left((1-\alpha)\sum_{j=1}^{p}\beta_j^2 + \alpha\sum_{j=1}^{p}|\beta_j|\right) \quad \textbf{Equation 11.7}$$

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, 0.10,
              0.15, 0.20, 0.30, 0.40, 0.50, 0.60, 0.80, 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** (Sajjadiani 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

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

KEITH LEAVITT
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.

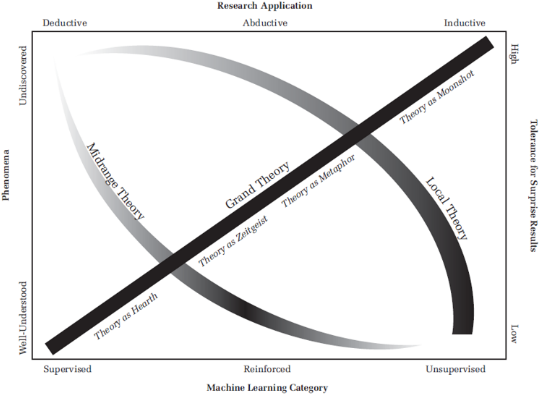
Source: Leavitt et al. (2021)

Data-driven Modeling in WOP

Epistemological Considerations

754 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?

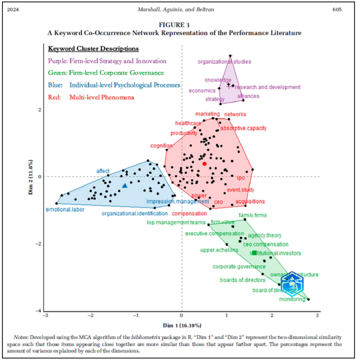
From Theory Proliferation to Theory Integration

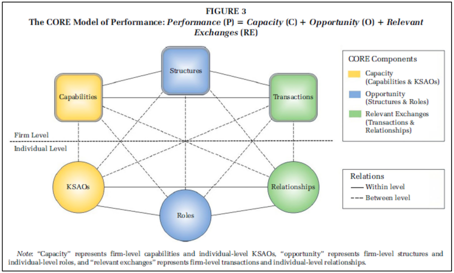
Inductive Approach for Integrating Performance Theories

- 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

Theory-driven modeling in WOP

Data-driven modeling in WOP

Towards an integration

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

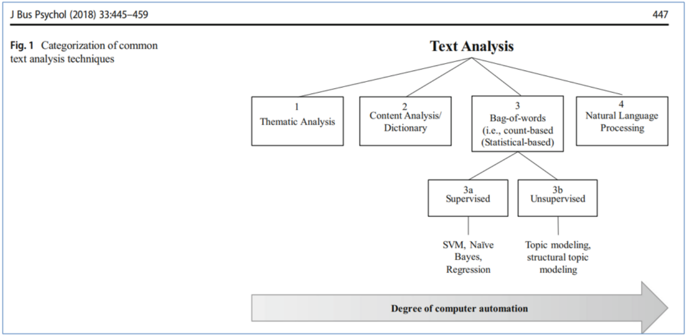
Some reasons

- 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)

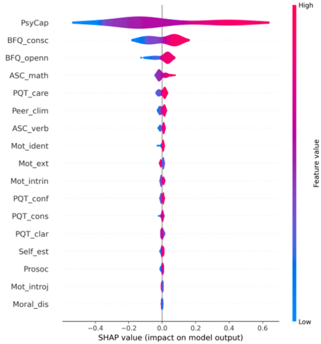
A Note on Explainable Artificial Intelligence (XAI)

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 37

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.).

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.).

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?
- Job Analysis: A cornerstone of WOP with a long history (Viteles, 1922), but it has received limited attention in recent research (Li et al., 2024; Putka et al., 2023). Could LLMs and predictive models help bridge the scientist-practitioner gap?
- Advancing studies on Performance Management Systems and related theories (e.g., predictions/outcomes of performance instability).

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?
- Job Analysis: A cornerstone of WOP with a long history (Viteles, 1922), but it has received limited attention in recent research (Li et al., 2024; Putka et al., 2023). Could LLMs and predictive models help bridge the scientist-practitioner gap?
- Advancing studies on Performance Management Systems and related theories (e.g., predictions/outcomes of performance instability).

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?
- Job Analysis: A cornerstone of WOP with a long history (Viteles, 1922), but it has received limited attention in recent research (Li et al., 2024; Putka et al., 2023). Could LLMs and predictive models help bridge the scientist-practitioner gap?
- Advancing studies on Performance Management Systems and related theories (e.g., predictions/outcomes of performance instability).

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?
- Job Analysis: A cornerstone of WOP with a long history (Viteles, 1922), but it has received limited attention in recent research (Li et al., 2024; Putka et al., 2023). Could LLMs and predictive models help bridge the scientist-practitioner gap?
- Advancing studies on Performance Management Systems and related theories (e.g., predictions/outcomes of performance instability).

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?
- Job Analysis: A cornerstone of WOP with a long history (Viteles, 1922), but it has received limited attention in recent research (Li et al., 2024; Putka et al., 2023). Could LLMs and predictive models help bridge the scientist-practitioner gap?
- Advancing studies on Performance Management Systems and related theories (e.g., predictions/outcomes of performance instability).

References I

Aguinis, H., & Cronin, M. A. (in press).It's the theory, stupid. *Organizational Psychology Review*. https://doi.org/10.1177/20413866221080629

Aguinis, H., Beltran, J. R., & Marshall, J. D. (2024).Performance: Confirming, refining, and refuting theories. *Journal of Management Scientific Reports*, *2*(2), 135–153. https://doi.org/10.1177/27550311241247487

Aguinis, H., Edwards, J. R., & Bradley, K. J. (2017).Improving our understanding of moderation and mediation in strategic management research. *Organizational Research Methods*, *20*(4), 665–685. https://doi.org/https://doi.org/10.1177/1094428115627498

Alessandri, G., Perinelli, E., Robins, R. W., Vecchione, M., & Filosa, L. (2020).Personality trait change at work: Associations with organizational socialization and identification. *Journal of Personality*, *88*(6), 1217–1234. https://doi.org/10.1111/jopy.12567

Allen, M. S., Robson, D. A., & Iliescu, D. (2023).Face validity: A critical but ignored component of scale construction in psychological assessment. *European Journal of Psychological Assessment*, *39*(3), 153–156. https://doi.org/10.1027/1015-5759/a000777

References II

Banks, G. C., Woznyj, H. M., Wesslen, R. S., & Ross, R. L. (2018). A review of best practice recommendations for text analysis in R (and a user-friendly app). *Journal of Business and Psychology*, *33*(4), 445–459. https://doi.org/10.1007/s10869-017-9528-3

Bauer, T., Erdogan, B., Caughlin, D., & Truxillo, D. (2024). *Human resource management: People, data, and analytics* (2nd ed.). Sage Publications.

Bliese, P. D., Certo, S. T., Smith, A. D., Wang, M., & Gruber, M. (2024). Strengthening Theory–Methods–Data links. *Academy of Management Journal*, *67*(4), 893–902. https://doi.org/10.5465/amj.2024.4004

Bollen, K. A. (1989). *Structural equations with latent variables*. Wiley. https://doi.org/10.1002/9781118619179

Borsboom, D. (2006). The attack of the psychometricians. *Psychometrika*, *71*(3), 425–440. https://doi.org/10.1007/s11336-006-1447-6

Brandmaier, A. M., & Jacobucci, R. C. (2023). Machine learning approaches to structural equation modeling. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (2nd ed., pp. 722–739). Guilford Press.

Braun, V., & Clarke, V. (2022). *Thematic analysis: A practical guide*. Sage.

References III

Breiman, L. (2001). Statistical modeling: The two cultures. *Statistical Science*, *16*(3), 199–215. https://doi.org/10.1214/ss/1009213726

Campion, M. A., & Campion, E. D. (2023). Machine learning applications to personnel selection: Current illustrations, lessons learned, and future research. *Personnel Psychology*, *76*(4), 993–1009. https://doi.org/10.1111/peps.12621

Caughlin, D. E. (2024). *R for HR: An introduction to human resource analytics using R* [Available at https://rforhr.com/].

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, *41*, 745–783. https://doi.org/10.1007/s10490-023-09871-y

Colquitt, J. A., Sabey, T. B., Rodell, J. B., & Hill, E. T. (2019). Content validation guidelines: Evaluation criteria for definitional correspondence and definitional distinctiveness.. *Journal of Applied Psychology*, *104*(10), 1243–1265. https://doi.org/10.1037/apl0000406

References IV

Cortina, J. M., Sheng, Z., Keener, S. K., Keeler, K. R., Grubb, L. K., Schmitt, N., Tonidandel, S., Summerville, K. M., Heggestad, E. D., & Banks, G. C. (2020).From alpha to omega and beyond! a look at the past, present, and (possible) future of psychometric soundness in the journal of applied psychology. *Journal of Applied Psychology*, *105*(12), 1351–1381. https://doi.org/10.1037/apl0000815

Edwards, M. R., Charlwood, A., Guenole, N., & Marler, J. (2024).HR analytics: An emerging field finding its place in the world alongside simmering ethical challenges. *Human Resource Management Journal*, *34*(2), 326–336. https://doi.org/10.1111/1748-8583.12435

Gonzalez, M. F., Capman, J. F., Oswald, F. L., Theys, E. R., & Tomczak, D. L. (2019).“Where's the I-O?”: Artificial intelligence and machine learning in talent management systems. *Personnel Assessment and Decisions*, *5*(3), 33–44. https://doi.org/10.25035/pad.2019.03.005

González-Romá, V., & Hernández, A. (2023).Conducting and evaluating multilevel studies: Recommendations, resources, and a checklist. *Organizational Research Methods*, *26*(4), 629–654. https://doi.org/10.1177/10944281211060

References V

Grand, J. A., Braun, M. T., & Kuljanin, G. (in press). Hello world! building computational models to represent social and organizational theory. *Organizational Research Methods*. https://doi.org/10.1177/10944281241261913

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424–438. https://doi.org/10.2307/1912791

Haig, B. D. (2020). Big data science: A philosophy of science perspective. In S. E. Woo, R. Proctor, & L. Tay (Eds.), *Big data methods for psychological research: New horizons and challenges* (pp. 15–33). American Psychological Association.

Hofmans, J., Morin, A. J. S., Breitsohl, H., Ceulemans, E., Chénard-Poirier, L. A., Driver, C. C., Fernet, C., Gagné, M., Gillet, N., González-Romá, V., Grimm, K. J., Hamaker, E. L., Hau, K.-T., Houle, S. A., Howard, J. L., Kline, R. B., Kuijpers, E., Leyens, T., Litalien, D., & Wille, B. (2021). The baby and the bathwater: On the need for substantive–methodological synergy in organizational research. *Industrial and Organizational Psychology*, *14*(4), 497–504. https://doi.org/10.1017/iop.2021.111

Hong, M., Jacobucci, R. C., & Lubke, G. (2020). Deductive data mining. *Psychological Methods*, *25*(6), 691–707. https://doi.org/10.1037/met0000252

References VI

- Jacobucci, R. C. (2022).A critique of using the labels confirmatory and exploratory in modern psychological research. *Frontiers in Psychology*, *13*, Article 1020770. https://doi.org/10.3389/fpsyg.2022.1020770
- Jacobucci, R. C., Grimm, K. J., & Zhang, Z. (2023). *Machine learning for social and behavioral research*. Guilford Press.
- Khan, N., & Millner, D. (2023). *Introduction to people analytics: A practical guide to data-driven HR* (2nd ed.). Kogan Page Publishers.
- Koenig, N., Tonidandel, S., Thompson, I., Albritton, B., Koohifar, F., Yankov, G., Speer, A., Hardy III, J. H., Gibson, C., Frost, C., et al. (2023).Improving measurement and prediction in personnel selection through the application of machine learning. *Personnel Psychology*, *76*(4), 1061–1123. https://doi.org/10.1111/peps.12608
- König, C., Demetriou, M., Glock, P., Hiemstra, A., Iliescu, D., Ionescu, C., Langer, M., Liem, C. C. S., Linnenbürger, A., Siegel, R., & Vartholomaios, I. (2020).Some advice for psychologists who want to work with computer scientists on big data. *Personnel Assessment and Decisions*, *6*(1), 17–23. https://doi.org/10.25035/pad.2020.01.002
- Kumar, L. S., & Burns, G. N. (2024).Determinants of safety outcomes in organizations: Exploring O*NET data to predict occupational accident rates. *Personnel Psychology*, *77*(2), 555–594. https://doi.org/10.1111/peps.12560

References VII

Lambert, L. S., & Newman, D. A. (2023). Construct development and validation in three practical steps: Recommendations for reviewers, editors, and authors. *Organizational Research Methods*, *26*(4), 574–607. https://doi.org/10.1177/10944281221115374

Landers, R. N., Auer, E. M., Dunk, L., Langer, M., & Tran, K. N. (2023). A simulation of the impacts of machine learning to combine psychometric employee selection system predictors on performance prediction, adverse impact, and number of dropped predictors. *Personnel Psychology*, *76*(4), 1037–1060. https://doi.org/10.1111/peps.12587

Landers, R. N., Auer, E. M., Collmus, A. B., & Marin, S. (2019). Data science as a new foundation for insightful, reproducible, and trustworthy social science. In R. N. Landers (Ed.), *Cambridge handbook of technology and employee behavior* (pp. 761–789). Cambridge University Press.

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

Leavitt, K., Schabram, K., Hariharan, P., & Barnes, C. M. (2021). Ghost in the machine: On organizational theory in the age of machine learning. *Academy of Management Review*, *46*(4), 750–777.

References VIII

Lee, P., Fyffe, S., Son, M., Jia, Z., & Yao, Z. (2023). A paradigm shift from "human writing" to "machine generation" in personality test development: An application of state-of-the-art natural language processing. *Journal of Business and Psychology*, *38*(1), 163–190. https://doi.org/10.1007/s10869-022-09864-6

Li, Y., Tuckey, M. R., Chen, P. Y., & Dollard, M. F. (2024). Job characteristics and employee outcomes: Criterion validity of the us occupational information network O*NET job analysis database in the australian context. *European Journal of Work and Organizational Psychology*, *33*(3), 325–339. https://doi.org/10.1080/1359432X.2024.2314923

Marshall, J. D., Aguinis, H., & Beltran, J. R. (2024). Theories of performance: A review and integration. *Academy of Management Annals*, *18*(2), 600–625. https://doi.org/10.5465/annals.2022.0049

McNulty, K. (2022). *Handbook of regression modeling in people analytics: With examples in R and Python*. Routledge.

Molnar, C. (2022). *Interpretable machine learning: A guide for making black box models explainable* (2nd ed.). Available at https://christophm.github.io/interpretable-ml-book/.

References IX

Morin, A. J., Bujacz, A., & Gagné, M. (2018). Person-centered methodologies in the organizational sciences: Introduction to the feature topic. *Organizational Research Methods*, *21*(4), 803–813. https://doi.org/10.1177/1094428118773856

Nesselroade, J. R., & Molenaar, P. C. (2016). Some behaviorial science measurement concerns and proposals. *Multivariate Behavioral Research*, *51*(2-3), 396–412. https://doi.org/10.1080/00273171.2015.1050481

Oswald, F. L., Behrend, T. S., Putka, D. J., & Sinar, E. (2020). Big data in Industrial-Organizational psychology and human resource management: Forward progress for organizational research and practice. *Annual Review of Organizational Psychology and Organizational Behavior*, *7*, 505–533. https://doi.org/10.1146/annurev-orgpsych-032117-104553

Paxton, A., & Griffiths, T. L. (2017). Finding the traces of behavioral and cognitive processes in big data and naturally occurring datasets. *Behavior Research Methods*, *49*, 1630–1638. https://doi.org/10.3758/s13428-017-0874-x

Perinelli, E., & Alessandri, G. (2020). A Latent State-Trait analysis of global self-esteem: A reconsideration of its state-like component in an organizational setting. *International Journal of Selection and Assessment*, *28*(4), 465–483. https://doi.org/10.1111/ijsa.12308

References X

Perinelli, E., Alessandri, G., Cepale, G., & Fraccaroli, F. (2022). The sociometer theory at work: Exploring the organizational interpersonal roots of self-esteem. *Applied Psychology: An International Review*, *71*(1), 76–102. https://doi.org/https://doi.org/10.1111/apps.12312

Putka, D. J., Beatty, A. S., & Reeder, M. C. (2018). Modern prediction methods: New perspectives on a common problem. *Organizational Research Methods*, *21*(3), 689–732. https://doi.org/10.1177/1094428117697041

Putka, D. J., Oswald, F. L., Landers, R. N., Beatty, A. S., McCloy, R. A., & Yu, M. C. (2023). Evaluating a natural language processing approach to estimating KSA and interest job analysis ratings. *Journal of Business and Psychology*, *38*(2), 385–410. https://doi.org/10.1007/s10869-022-09824-0

Rönkkö, M., & Cho, E. (2022). An updated guideline for assessing discriminant validity. *Organizational Research Methods*, *25*(1), 6–14. https://doi.org/10.1177/1094428120968614

Rossiter, J. R. (2008). Content validity of measures of abstract constructs in management and organizational research. *British Journal of Management*, *19*(4), 380–388. https://doi.org/10.1111/j.1467-8551.2008.00587.x

References XI

Sajjadiani, S., Sojourner, A. J., Kammeyer-Mueller, J. D., & Mykerezi, E. (2019). Using machine learning to translate applicant work history into predictors of performance and turnover. *Journal of Applied Psychology, 104*(10), 1207–1225. https://doi.org/10.1037/apl0000405

Schaufeli, W. B., Shimazu, A., Hakanen, J., Salanova, M., & De Witte, H. (2017). An ultra-short measure for work engagement: The UWES-3 validation across five countries. *European Journal of Psychological Assessment, 35*(4), 577–591. https://doi.org/10.1027/1015-5759/a000430

Serang, S., Jacobucci, R. C., Brimhall, K. C., & Grimm, K. J. (2017). Exploratory mediation analysis via regularization. *Structural Equation Modeling: A Multidisciplinary Journal, 24*(5), 733–744. https://doi.org/10.1080/10705511.2017.1346838

Sheetal, A., Jiang, Z., & Di Milia, L. (2023). Using machine learning to analyze longitudinal data: A tutorial guide and best-practice recommendations for social science researchers. *Applied Psychology: An International Review, 72*(3), 1339–1364. https://doi.org/10.1111/apps.12435

Shmueli, G. (2010). To explain or to predict? *Statistical Science, 25*(3), 289–310. https://doi.org/10.1214/10-STS330

References XII

Somaraju, A. V., Nye, C. D., & Olenick, J. (2022). A review of measurement equivalence in organizational research: What's old, what's new, what's next? *Organizational Research Methods*, *25*(4), 741–785. https://doi.org/10.1177/10944281211056524

Song, Q. C., Oh, I.-S., Kim, Y., & So, C. (in press). Revisiting the nature and strength of the personality–job performance relations: New insights from interpretable machine learning. *Journal of Applied Psychology*. https://doi.org/10.1037/apl0001218

Spector, P. E. (2017). *Industrial and organizational psychology: Research and practice* (7th ed.). John Wiley & Sons.

Stanghellini, F., Perinelli, E., Lombardi, L., & Stella, M. (2024). Introducing semantic loadings in factor analysis: Bridging network psychometrics and cognitive networks for understanding depression, anxiety and stress. *advances.in/psychology*, *2*, Article e35366. https://doi.org/10.56296/aip00008

Starbuck, C. (2023). *The fundamentals of people analytics: With applications in R*. Springer.

Thatcher, S. M. B., Pfarrer, M. D., & Devers, C. E. (2024). Breaking news: JOM wants your theory papers. *Journal of Management*, *50*(4), 1183–1185. https://doi.org/10.1177/01492063241227422

References XIII

Tonidandel, S., King, E. B., & Cortina, J. M. (2016). *Big data at work: The data science revolution and organizational psychology*. Routledge.

Tonidandel, S., King, E. B., & Cortina, J. M. (2018). Big data methods: Leveraging modern data analytic techniques to build organizational science. *Organizational Research Methods*, *21*(3), 525–547. https://doi.org/10.1177/1094428116677299

Tonidandel, S., Summerville, K. M., Gentry, W. A., & Young, S. F. (2022). Using structural topic modeling to gain insight into challenges faced by leaders. *The Leadership Quarterly*, *33*(5), Article 101576. https://doi.org/10.1016/j.leaqua.2021.101576

van Dongen, N., van Bork, R., Finnemann, A., Haslbeck, J. M. B., van der Maas, H. L. J., Robinaugh, D. J., de Ron, J., Sprenger, J., & Borsboom, D. (in press). Productive explanation: A framework for evaluating explanations in psychological science. *Psychological Review*. https://doi.org/10.1037/rev0000479

van Roekel, H., Wigger, E. F., Veldkamp, B. P., & Bakker, A. B. (2024). What is work engagement? A text mining approach using employees' self-narratives. *Applied Psychology: An International Review*, *73*(3), 1071–1102. https://doi.org/10.1111/apps.12501

References XIV

- Viteles, M. S. (1922). Job specifications and diagnostic tests of job competency designed for the auditing division of a street railway company: A psychological study in industrial guidance. *The Psychological Clinic, 14*(3-4), 83–105.
- Woo, S. E., Tay, L., & Oswald, F. (in press). Artificial intelligence, machine learning, and big data: Improvements to the science of people at work and applications to practice. *Personnel Psychology*. https://doi.org/10.1111/peps.12643
- Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science, 12*(6), 1100–1122. https://doi.org/10.1177/1745691617693393
- Zhou, L., Wang, M., & Zhang, Z. (2021). Intensive longitudinal data analyses with Dynamic Structural Equation Modeling. *Organizational Research Methods, 24*(2), 219–250. https://doi.org/10.1177/1094428119833164
- Zyphur, M. J., Bonner, C. V., & Tay, L. (2023). Structural equation modeling in organizational research: The state of our science and some proposals for its future. *Annual Review of Organizational Psychology and Organizational Behavior*, *10*, 495–517. https://doi.org/10.1146/annurev-orgpsych-041621-031401

Thanks for your attention

enrico.perinelli@unitn.it

UNIVERSITÀ DI TRENTO
Dipartimento di Psicologia e Scienze Cognitive

Associazione Italiana di Psicologia