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978-1-107-04315-2 - Best-Worst Scaling: Theory, Methods and Applications

Jordan J. Louviere, Terry N. Flynn and A. A. J. Marley

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BEST-WORST SCALING

Best-Worst Scaling (BWS) is an extension of the method of paired comparison to multiple choices that asks participants to choose both the most and the least attractive options or features from a set of choices. It is an increasingly popular way for academics and practitioners in social science, business, and other disciplines to study and model choice. This book provides an authoritative and systematic treatment of best-worst scaling, introducing readers to the theory and methods for three broad classes of applications. It uses a variety of case studies to illustrate simple but reliable ways to design, implement, apply, and analyze choice data in specific contexts, and showcases the wide range of potential applications across many different disciplines. Best-worst scaling avoids many rating scale problems and will appeal to those wanting to measure subjective quantities with known measurement properties that can be easily interpreted and applied.

JORDAN J. LOUVIERE is Research Professor, School of Marketing, UniSA Business School, University of South Australia. He is particularly known for pioneering work in the design and application of discrete choice experiments (also called “choice-based conjoint”) and he also pioneered best-worst scaling (also known as “Max-Diff Scaling”). He is co-author of *Stated Choice Methods: Analysis and Application* (Cambridge University Press, 2000).

TERRY N. FLYNN PhD is the Director of TF Choices Ltd (UK) and Adjunct Fellow at the University of Western Sydney (Australia). He is globally renowned in the use of discrete choice experiments and best-worst scaling in health and allied fields. He is also a world expert in the scoring of quality of life and end-of-life instruments, particularly using BWS, and is a founding member of the International Academy of Health Preference Research.

A. A. J. MARLEY is Adjunct Professor in the Department of Psychology, University of Victoria and Research Professor at The Institute for Choice, University of South Australia. He is particularly known for his work in probabilistic models of choice, perception, and voting. He is a co-author of *Behavioral Social Choice: Probabilistic Models, Statistical Inference, and Applications* (Cambridge University Press, 2006).

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BEST-WORST SCALING
Theory, Methods and Applications

JORDAN J. LOUVIERE, TERRY N. FLYNN AND A. A. J. MARLEY
(With Invited Chapters on Applications)



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Contributors to application chapters

Richard T. Carson: Professor, Department of Economics, University of California, San Diego

Eli Cohen: Associate Professor, Department of Management, Gilford Glazer Faculty of Management, Ben Gurion University of the Negev, Israel, and Ehrenberg Bass Institute for Marketing Science, University of South Australia

Charles Corke: Intensive Care Specialist, Barwon Health, Australia

Terry N. Flynn: Director of TF Choices Ltd (UK) and Adjunct Fellow, University of Western Sydney

Bart D. Frischknecht: VP Research and Customer Success, Vennli, South Bend, Indiana

Elisabeth Huynh: Postdoctoral Fellow, Institute for Choice, University of South Australia

Towhidul Islam: University Research Chair, Professor and Graduate Coordinator of the Department of Marketing and Consumer Studies, College of Business and Economics, University of Guelph, Canada

Larry Lockshin: Professor, Ehrenberg Bass Institute for Marketing Science, University of South Australia

Jordan J. Louviere: Professor, School of Marketing, University of South Australia

Janet R. McColl-Kennedy: Professor of Marketing, UQ Business School, University of Queensland

Emma McIntosh: Reader in Health Economics of Public Health, Institute of Health and Wellbeing, University of Glasgow

Geoffrey N. Soutar: Winthrop Professor of Marketing and Head of Discipline, University of Western Australia Business School

Jillian C. Sweeney: Winthrop Professor of Marketing, University of Western Australia Business School

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Preface

Jordan J. Louviere first proposed best-worst scaling (BWS) in the late 1980s as a way to capitalize on humans' tendency to be more reliable and accurate at identifying extreme options. Louviere first called the method maximum difference scaling, to describe what he hypothesized as the underlying process, namely choosing the pair of stimuli in a set of stimuli that exhibited the largest subjective difference on the underlying continuum of interest. Since that time BWS has been adopted by academics and practitioners in many fields globally. However, marketing researchers continue to refer to it as maximum difference scaling (or "maxdiff"), while academics have overwhelmingly now begun to call it best-worst scaling. Louviere and colleagues changed the name to reflect the fact that years of academic research had made it clear that no one actually used a maximum difference choice process, so a much better general term for the method was BWS.

So, BWS now is almost 25 years old. The current authors began receiving numerous requests for assistance and explanations about how to do BWS around 2005; such requests have continued unabated since then. It became clear from the requests, comments and interactions in BWS and more conventional choice modelling short courses that there was a need for a book that brought BWS theory and methods together in such a way that as many people as possible could learn the basic theory and ways to design, implement and analyze BWS experiments in as simple a pedagogical manner as possible. Therefore, this book began with many discussions between Louviere, Flynn and Marley about the need for such a book, leading to them spending time together in the Seattle, Washington, area in 2009 to begin the writing process. That led to discussions about the need for application chapters, which in turn led to invitations to various researchers, principally academics, who were early adopters of BWS, to contribute such chapters.

So, our key reason for writing the book was to introduce as many people as possible to choice-based measurement methods (of which BWS is one type) with the hope of eventually eliminating the many atheoretical and ad hoc measurement methods that are applied in the social and business disciplines. BWS provides a theoretical framework to measure latent, subjective quantities that can produce measurement values with known properties. The theory can be tested and falsified; hence, if the theory is a good first approximation to

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the underlying choice process(es) being studied, one can have confidence in the measurement properties of the derived values. Unfortunately, one cannot falsify ad hoc measurement methods such as category rating scales. Indeed, it is surprising how uncritical their use is by so many academics and practitioners, especially in light of the fact that, despite some past attempts, it is unlikely that there will ever be a theory from first principles that represents the process by which humans produce category ratings values in response to various stimuli and/or experimental manipulations of interest. More importantly, BWS can replace category rating scales in most commercial and academic applications, and our hope is that we will eventually see many ad hoc measurement methods replaced by BWS.

We hope that those who read this book will be inspired that it is possible to develop and apply theory-based measurement methods in the social and business sciences. We think that the book is important because it finally puts forth a theoretically sound measurement method that can be used in virtually all academic and commercial research applications in which category rating scales currently are used. Better yet, BWS measurement tasks are simple, reliable and accurate, and at the worst require a few more evaluations than category rating scales in almost all cases. As we also note in the book, BWS has been compared with and tested against category rating scales, and virtually every comparison of which we are aware has strongly favored BWS, with the exception that it typically takes humans longer to do BWS tasks. While there are some who see the extra time BWS takes to be a problem, we see this, instead, as a serious opportunity, because it suggests that in many instances the humans involved in the tasks are taking them seriously. Therefore, it is not at all obvious that the fact that BWS tasks take longer for humans to do is a bad thing.

We also hope that the book will inspire some to see the many research opportunities that remain, and take on the task of filling in the research gaps that we note in Chapter 6. It is also our hope that many with backgrounds in psychometrics will see clear opportunities to use BWS tasks where they currently use rating scales and matching tasks. Likewise, and without further comment, we would like to suggest that it may well be in the interest of psychometricians and scale developers to consider whether one can use BWS to replace the current process of selecting items using various factor-analytic and related methods. We also note in passing that “structural choice models” provide statistical theory that integrates structural equation modeling with choice modeling and choice tasks (Rungie, Coote and Louviere, 2011; 2012). BWS is a natural fit to these types of models. So, theory and methods currently are in place to take advantage of the BWS choice-based measurement approach.

Acknowledgments

Writing a book such as this one necessarily involves many people besides the authors.

We would like to acknowledge the considerable contributions made by Edward Wei, who was the head of the online survey programming team in the Institute for Choice (also known as I4C) until recently. During his tenure with the Institute for Choice team, Edward developed many innovative new ways to greatly enhance online surveys and consequently the ability to be at the forefront of online survey work for discrete choice experiments and BWS globally.

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Ultimately, the responsibility for the book and its contents rests with us. We welcome feedback and suggestions for improving potential future editions. The primary goal of this first edition is to communicate in the simplest way we know how, so as to allow the widest possible audience to be able to understand and apply the theory and methods. We hope we have achieved this goal, but we also know that we will hear from you if we have not.