Let’s talk about Thurstone & Co.: An information-theoretical model for comparative judgments, and its statistical translation

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Abstract

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# Introduction

In *comparative judgment* (CJ) studies, judges assess a specific trait or attribute across various stimuli by performing pairwise comparisons (Thurstone 1927b, 1927a). Each comparison produces a dichotomous outcome, indicating which stimulus is perceived to exhibit a higher trait level. For example, when assessing text quality, judges compare pairs of written texts (the stimuli) to determine the relative quality each text exhibit (the trait) (Laming 2004; Pollitt 2012; Whitehouse 2012; van Daal et al. 2016; Lesterhuis 2018a; Coertjens et al. 2017; Goossens and De Maeyer 2018; Bouwer et al. 2023).

Numerous studies have documented the effectiveness of CJ in assessing traits and competencies over the past decade. These studies have emphasized three aspects of the method’s effectiveness: its reliability, validity, and practical applicability. Research on reliability indicates that CJ requires a relatively small number of pairwise comparisons (S. Verhavert et al. 2019; Crompvoets, Béguin, and Sijtsma 2022) to produce trait scores that are as precise and consistent as those generated by other assessment methods (Coertjens et al. 2017; Goossens and De Maeyer 2018; Bouwer et al. 2023). Furthermore, evidence suggests that the reliability and time efficiency of CJ are comparable, if not superior, to those of other assessment methods when employing adaptive comparison algorithms (Pollitt 2012; San Verhavert, Furlong, and Bouwer 2022; Mikhailiuk et al. 2021). On the other hand, research on validity suggests that scores generated by CJ can accurately represent the traits under measurement (Whitehouse 2012; van Daal et al. 2016; Lesterhuis 2018a; Bartholomew et al. 2018; Bouwer et al. 2023). Finally, research on practical applicability highlights the method’s versatility across both educational and non-educational contexts (Kimbell 2012; Jones and Inglis 2015; Bartholomew et al. 2018; Jones et al. 2019; Marshall et al. 2020; Bartholomew and Williams 2020; Boonen, Kloots, and Gillis 2020).

Nevertheless, despite the increasing number of CJ studies, unsystematic and fragmented research approaches have left several critical issues unaddressed. This research primarily focuses on three: the over-reliance on Thurstone’s Case V assumptions in the statistical analysis of CJ data, the apparent disconnect between CJ’s trait measurement and hypothesis testing, and the unclear role of comparison algorithms on the method’s reliability and validity. The following sections will discuss each of these issues in detail, followed by the introduction of a theoretical model and its statistical translation, which aims to address all three concerns simultaneously.

# Three critical issues in CJ literature

In its most general form, Thurstone’s theory (1927a) posits that the dichotomous outcome resulting from comparing two stimuli is determined by two factors: the discriminal process of each stimulus and their discriminal difference. The *discriminal process* refers to the psychological effect each stimulus has on the judges, or more simply stated, the judges’ perception of the trait level of each stimulus. Thurstone assumes that the discriminal process for each stimulus follows a Normal distribution. In this distribution, the mode (mean), known as the *modal discriminal process*, represents the position of the stimulus on the trait continuum, while the dispersion, known as the *discriminal dispersion*, reflects the variability in the stimulus’ perceived trait level. [Figure 1](#fig-discriminal_process) shows example distributions of discriminal process for two stimuli (objects).

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| Figure 1: Example distributions of discriminal processes for two stimuli (objects). Extracted from Bramley (2008, 249). |

However, since the discriminal mode and dispersion of a single stimulus are not directly observable except through comparison, the *law of comparative judgment* becomes essential. This law asserts that when assessing a specific trait by comparing two stimuli, the stimulus positioned further along the continuum is perceived as having a higher level of that trait. Thus, the observed dichotomous outcome is determined by the distribution of the difference between the stimuli’s discriminal processes, called the *discriminal difference*. [Figure 2](#fig-comparative_judgment) shows an example distribution of the discriminal difference for two stimuli (objects).

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| Figure 2: Distribution of the discriminal difference between two stimuli (objects). Extracted from Bramley (2008, 251). |

Importantly, the theory’s general form primarily addresses pairwise comparisons of stimuli made by a single judge (Thurstone 1927a, 267). Consequently, to enhance its practical applicability, Thurstone introduced five distinct cases, each defined by progressively simplifying assumptions. [Table 1](#tbl-thurstone_cases) summarizes these cases, focusing on key assumptions such as the distribution of discriminal processes, the similarity of discriminal dispersions across stimuli, the correlation between stimuli, and which judges perform the comparisons. For a comprehensive discussion of this progression, refer to Thurstone (1927a) and Bramley (2008, 248–53).

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| Table 1: Thurstones cases and asumptions |

## The Case V and the statistical analysis of CJ data

Surprisingly, despite its reliance on the largest number of simplifying assumptions (Bramley 2008, 253; Kelly, Richardson, and Isaacs 2022, 677), Case V remains the most widely used case in the CJ literature. This popularity is largely due to its simplified statistical representation in the Bradley-Terry-Luce (BTL) model (Bradley and Terry 1952; Luce 1959). The BTL model mirrors Case V’s assumptions, with one key difference: while Case V assumes a Normal distribution for the stimuli’s discriminal processes, the BTL model uses the more mathematically tractable Logistic distribution (Andrich 1978; Bramley 2008, 254) (see [Table 1](#tbl-thurstone_cases)). This substitution has little effect on the model’s estimation or interpretation, as the Normal and Logistic distributions differ by a scaling factor of approximately (van der Linden 2017, 1:16) (refer to [Figure 3](#fig-logistic_vs_normal)).

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| |  | | --- | | (a) Probability density | |  |

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| --- | --- |
| |  | | --- | | (b) Cummulative probability | |

Figure 3: Probability density and cumulative probability of the logistic and Normal distributions. Extracted from Bramley (2008, 254–55).

However, Case V was originally developed to provide a “rather coarse scaling” of traits (Thurstone 1927a, 269), prioritizing statistical simplicity over precision in trait measurement (Kelly, Richardson, and Isaacs 2022, 677). As a result, its assumptions may not suit applications beyond the psycho-physical contexts for which it was created. Thurstone himself cautioned that its use “should not be made without experimental test” (Thurstone 1927a, 270), acknowledging that some assumptions could prove problematic with complex traits or less homogeneous stimuli (Thurstone 1927b, 374). Consequently, given that current CJ applications often deal these types of traits and stimuli, two key assumptions of Case V may not consistently hold in theory or practice: the zero correlation and equal dispersion between stimuli.

The assumption of *zero correlation between stimuli* is best illustrated with an example. For instance, when evaluating text quality, the assumption suggests that a judge’s perception of quality in one text does not influence the perception of the same trait in the comparison text. Thurstone attributes this independence to the cancellation of potential judges’ biases, driven by opposing and equally weighted factors that operate during pairwise comparisons, called ‘mood’ and ‘simultaneous contrast’ effects (Thurstone 1927a, 268). This cancellation of bias has been mathematically demonstrated by Andrich (1978), assuming discriminal processes with additive biases and a logit scale derived from the BTL model.

However, two types of scenarios make it plausible that potential judges’ biases may not cancel: those involving complex traits and less homogeneous stimuli, and those where judges differ in what they value in their assessments. In the first scenario, Thurstone noted that for complex traits and non-homogeneous stimuli, such as handwriting or English compositions, CJ data might not align with the assumptions of Case V (Thurstone 1927b, 374). This insight likely extends to other similarly complex traits and stimuli. In the second scenario, evidence indicates that judges’ assessments are influenced by multiple, intricate aspects of the stimuli (van Daal et al. 2016; Lesterhuis 2018b; Chambers and Cunningham 2022). Moreover, factors like age, culture, education, expertise (Kelly, Richardson, and Isaacs 2022, 683), and even individual differences among judges (Gill and Bramley 2013; van Daal et al. 2017; van Daal 2020) can influence judgment accuracy. These scenarios can ultimately result in non-additive biases that resist cancellation, driven by the characteristics or location of stimuli within the trait continuum.

This also translates into the idea that stimuli are the main focus of estimation and analysis, but what happens when the focus of analysis is the individuals that generated those stimuli. Meaning there is an amount of correlation that it is not accounted for. Use example of Boonen!!

Such differences may not be detected through analyses of bias and misfit (Kelly, Richardson, and Isaacs 2022, 683).

## The disconnect between trait measurement and hypothesis testing

Building on the previous section, it is evident that the BTL model commonly functions as the measurement model for the trait of interest in CJ experiments (Andrich 1978; Bramley 2008). A measurement model specifies how manifest variables contribute to the estimation of latent variables (Everitt and Skrondal 2010). For example, when evaluating text quality, researchers use the BTL model to process the dichotomous outcomes resulting from the pairwise comparisons (the manifest variables) to estimate scores that reflect the underlying quality level of texts (the latent variable) (Laming 2004; Pollitt 2012; Whitehouse 2012; van Daal et al. 2016; Lesterhuis 2018a; Coertjens et al. 2017; Goossens and De Maeyer 2018; Bouwer et al. 2023).

Researchers then typically use the estimated BTL scores, or their transformations, to conduct additional analyses or hypothesis tests. For example, these scores have been used to identify ‘misfit’ judges and stimuli (Pollitt 2012; van Daal et al. 2017; Goossens and De Maeyer 2018), detect biases in judges’ ratings (Pollitt and Elliott 2003; Pollitt 2012), calculate correlations with other assessment methods (Goossens and De Maeyer 2018; Bouwer et al. 2023), or test hypotheses related to the underlying trait of interest (Bramley and Vitello 2019; Boonen, Kloots, and Gillis 2020; Bouwer et al. 2023; van Daal et al. 2017; Jones et al. 2019; Gijsen et al. 2021).

However, the statistical literature advises caution when using estimated scores to conduct additional analyses or hypotheses tests. A key consideration is that BTL scores are parameter estimates that inherently carry uncertainty. Ignoring this uncertainty can introduce bias into the analysis and reduce the precision of hypothesis tests. Notably, the direction and magnitude of the bias are often unpredictable; results may be attenuated, exaggerated, or remain unaffected, depending on the amount of uncertainty present in the scores and the actual effects being tested (Kline 2023, 25; Hoyle 2023, 137). Furthermore, reduced precision in hypothesis tests weakens their statistical power, ultimately increasing the likelihood of committing type-I or type-II errors (McElreath 2020).

To mitigate these risks, principles from Structural Equation Modeling (SEM) (Hoyle 2023, 138) and Item Response Theory (IRT) (Fox 2010, chap. 6; van der Linden 2017, vol. 1, chap. 24) recommend conducting these analyses and tests within a structural model. A structural model specifies how different manifest or latent variables influence the latent variable of interest (Everitt and Skrondal 2010). This approach allows analyses that can account for both the BTL scores and their uncertainties simultaneously, rather than treating them as separate elements. Therefore, an integrated approach that combines CJ’s measurement and structural models can offer significant advantages.

## The role and impact of comparison algorithms

# Theory

## A theoretical model for CJ

## From theory to statistics

# Discussion

## Findings

## Limitations and further research

# Conclusion

# Declarations

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# Appendix

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