

Causes and effects in Dichotomous Comparative Judgments: an information-theoretical system with plausible mechanism

Jose Manuel Rivera Espejo^{a,*}, Tine van Daal^a, Sven De Maeyer^a, Steven Gillis^b

^a*University of Antwerp, Training and education sciences,*

^b*University of Antwerp, Linguistics,*

Abstract

Dichotomous Comparative Judgment (DCJ) requires judges to compare pairs of stimuli to determine which one exhibits a higher degree of a specific trait. DCJ has proven effective and reliable across various fields (Pollitt, 2012b; Jones, 2015; van Daal et al., 2019; Bartholomew et al., 2018; Lesterhuis, 2018; Bartholomew and Williams, 2020; Marshall et al., 2020; Boonen et al., 2020). However, despite the method's widespread use, existing literature lacks a clear explanation of the complexities and assumptions underpinning the DCJ system, as well as the plausible mechanisms through which DCJ data could be generated. This study addresses these issues by representing DCJ within the framework of causal inference. Specifically, utilizing the structural approach, the study develops a scientific model to clarify the causal assumptions and mechanisms inherent in the DCJ system. It then translates this model into a probabilistic statistical framework to estimate statistical relationships and infer causal effects within the system. This research provides a robust probabilistic foundation for the statistical analysis of DCJ data, building upon Thurstone's law of comparative judgment (1927). Its findings offer valuable insights for researchers and analysts designing and implementing DCJ experiments.

Keywords: comparative judgement, directed acyclic graph, causal analysis, probabilistic statistics

1. Introduction

In contemporary contexts, Thurstone's law of comparative judgment (1927) primarily refers to the method of *dichotomous* comparative judgment (DCJ, Pollitt, 2012a,b). In DCJ, a judge assesses the relative manifestation of a *trait* within a pair of stimuli. This assessment results in a dichotomous value indicating which stimulus possesses a higher degree of the trait. After different judges perform multiple rounds of pairwise

*Corresponding author

Email addresses: JoseManuel.RiveraEspejo@uantwerpen.be (Jose Manuel Rivera Espejo),
tine.vandaal@uantwerpen.be (Tine van Daal), sven.demaeyer@uantwerpen.be (Sven De Maeyer),
steven.gillis@uantwerpen.be (Steven Gillis)

Preprint submitted to Psychometrika

July 26, 2024

comparisons, an outcome vector is produced. This vector is modeled using the Bradley-Terry-Luce model (BTL, [Bradley and Terry, 1952](#); [Luce, 1959](#)), which creates a score that corresponds with the trait of interest. This score is then used to rank the stimuli from lowest to highest or to evaluate the influence of certain variables on the stimuli's positions in the ranking.

DCJ has proven effective in assessing competencies and traits predominantly within the educational realm, as demonstrated by [Pollitt \(2012b\)](#), [Jones \(2015\)](#), [van Daal et al. \(2019\)](#), [Bartholomew et al. \(2018\)](#), [Lesterhuis \(2018\)](#), [Bartholomew and Williams \(2020\)](#), and [Marshall et al. \(2020\)](#). However, its application transcends education, as exemplified by [Boonen et al. \(2020\)](#). The methodology has also evolved to include multiple, as opposed to pairwise comparisons ([Luce, 1959](#); [Plackett, 1975](#)), and to accommodate comparisons with ordinal outcomes ([Tutz, 1986](#); [Agresti, 1992](#)). Overall, research suggests that DCJ offers an alternative and efficient approach to measurement and evaluation, characterized by its reliability and validity ([Lesterhuis, 2018](#); [van Daal, 2020](#); [Marshall et al., 2020](#)). Nevertheless, despite the method's widespread use, existing literature lacks a clear representation of the plausible mechanisms through which DCJ data could be generated. Particularly, there is no depiction of the complexity and the assumptions underpinning the DCJ system, nor how different assessment factors can potentially influence the observed DCJ outcome.

According to [Verhavert et al. \(2019\)](#) and [van Daal \(2020\)](#), several assessment factors interact and influence the method's outcome. These factors include the number and characteristics of the stimuli, their *proximity* in terms of the assessed trait, the number of comparison per stimulus, and the pairing algorithm used. Furthermore, since the method relies on judges' assessments, the number and characteristics of judges, their *discrimination* abilities, and the number of comparisons per judge also play pivotal roles. Moreover, when the stimuli represent sub-units of higher-levels units, factors such as the number and characteristics of these units, along with their *proximity* in terms of the assessed trait, can significantly influence the outcome. For instance, [van Daal et al. \(2019\)](#) assessed academic writing skills of university students (units) using multiple argumentative essays (sub-units).

Although several studies have examined the individual impact of these factors on the method's reliability ([Bramley, 2015](#); [Pollitt, 2012b](#); [Bramley and Vitello, 2019](#); [Verhavert et al., 2019](#); [Crompvoets et al., 2022](#); [van Daal et al., 2017](#); [Gijzen et al., 2021](#)), none, to the best of the authors' knowledge, have provided a transparent depiction of the DCJ system and the mechanisms generating the DCJ outcome. This study aims to fill this gap by representing DCJ within the framework of causal inference. Specifically, utilizing the structural approach ([Wright, 1927](#); [Pearl, 2009](#); [Pearl et al., 2016](#)), the study develops a scientific model to clarify the causal assumptions and mechanisms inherent in the DCJ system. Next, using a minimal set of assumptions, the study translates the scientific model into a probabilistic statistical model. This model aims to produce statistical estimates to draw inferences about plausible causal relationships within the DCJ system.

Ultimately, this research provides a robust probabilistic foundation for the statistical analysis of DCJ data, building upon Thurstone's law of comparative judgment ([1927](#)). Consequently, its findings offer valuable insights for researchers and analysts designing and implementing DCJ experiments.

2. Theoretical background

2.1. The structural approach to causal inference

In statistics, *causal inference* refers to the process of identifying the causes of a phenomenon and estimating their effects using data (Shaughnessy et al., 2010; Neal, 2020). Unlike classical statistical modeling, which focuses solely on summarizing data and inferring associations, causal inference provides a coherent mathematical notation for analyzing causes and counterfactuals (Pearl, 2009).

Counterfactuals represent scenarios *contrary to fact*, where alternative *potential* outcomes resulting from a cause are neither observed nor observable (Neal, 2020; Counterfactual, 2024). According to Pearl and Mackenzie (2018), counterfactuals form the foundation of causal inference and occupy the highest level of cognitive abstraction in the ladder of causation, followed by intervention and association. Despite this abstract nature, counterfactuals enable the development of a *theory of the world* that explains why specific causes have specific effects and what occurs in their absence (Pearl and Mackenzie, 2018). They achieve this by translating causal statements into counterfactual statements, that is, statements about “what would have happened in the world under different circumstances.”

Several approaches to causal inference and counterfactuals exist, but two are particularly prominent: the potential outcomes approach, also known as the Neyman-Rubin causal model (Neyman, 1923; Rubin, 1974), and the structural approach (Wright, 1927; Pearl, 2009; Pearl et al., 2016). Both approaches employ rigorous mathematical notation to characterize causal inference, but they do so in different ways (Neal, 2020). The potential outcomes approach relies on counterfactual notation, whereas the structural approach employs the do-operator and structural causal models (SCM, Pearl, 2009; Pearl et al., 2016). Despite these differences, both notations can be expressed in terms of the other, and both approaches provide methods for using experimental and observational data to estimate causal effects (Pearl, 2010).

Nevertheless, the structural approach offers an additional key advantage over the potential outcomes approach: it enables the graphical representation of any system through directed acyclic graphs (DAG, Gross et al., 2018; Neal, 2020). DAGs are heuristics that can effectively convey the assumed causal structure of a system. They do not represent detailed statistical models but allow researchers to deduce which statistical models can provide valid causal inferences, assuming the causal structure depicted in the DAG is accurate (McElreath, 2020).

2.2. DAGs, SCMs, and the flow of association and causation

Graph theory is a branch of mathematics focused on the study of graphs. Graphs are mathematical structures that model pairwise relations between objects. They can represent physical relations, such as electrical circuits and roadways, and less tangible structures, such as ecosystems and sociological relations (Gross et al., 2018). Graphs have proven useful in various fields, spanning statistics, computer science, operations research, and the natural and social sciences. One application in statistics that incorporates concepts from graph theory is causal inference. Specifically, the structural approach to

causal inference uses directed acyclic graphs (DAG) to provide a formal and graphical representation of the causal structure of a system (Neal, 2020).

A graph is a collection of nodes connected by edges. In a directed graph, edges extend from a *parent* node to a *child* node, with arrows indicating the direction of the causal influence. Two nodes that are connected by edge are said to be *adjacent* (Gross et al., 2018). In a directed acyclic graph (DAG), the direction of causal influences does not loop back on itself, ensuring that the graph contains no cycles (Neal, 2020; McElreath, 2020).

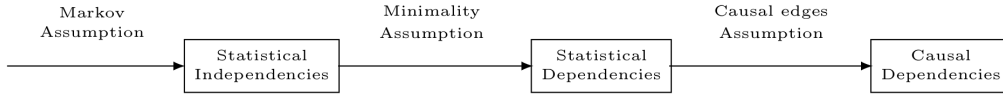


Figure 1: The flow of association and causation in graphs. Extracted from Neal (2020, 31)

2.3. But where does it all fit?

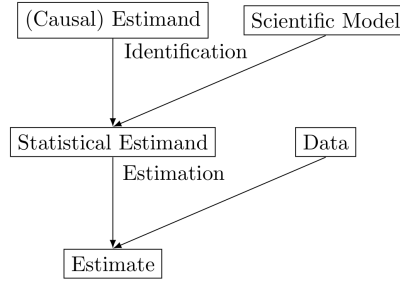


Figure 2: Identification-Estimation flowchart. Extracted from Neal (2020, 32)

3. Theoretical framework

3.1. A scientific model for the DCJ

3.2. Probabilistic assumptions of the scientific model

3.3. From the scientific to statistical model

3.4. Let's talk about Thurstone

4. Discussion

4.1. Findings

4.2. Limitations and further research

5. Conclusion

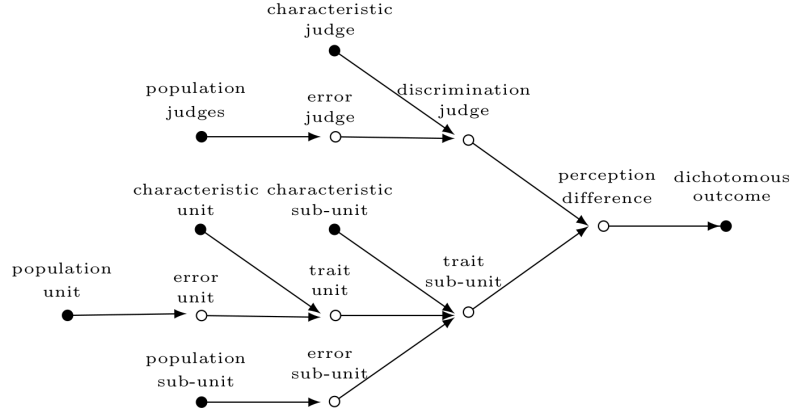


Figure 3: DCJ causal diagram, simplified description

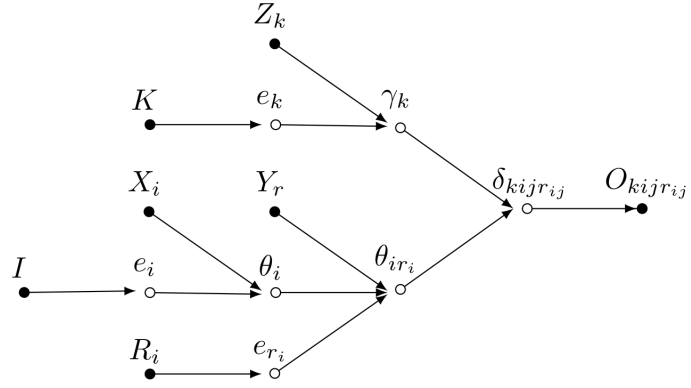


Figure 4: DCJ causal diagram, simplified mathematical description

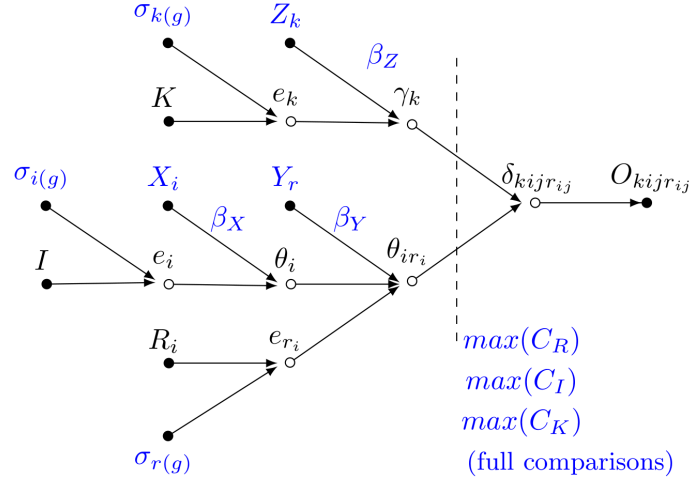


Figure 5: DCJ causal diagram, population mathematical description

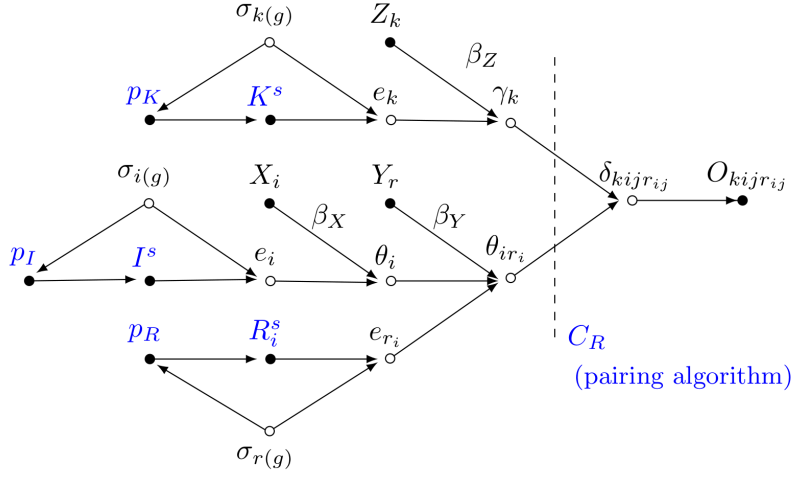


Figure 6: DCJ causal diagram, sample with comparisons mathematical description

Declarations

Funding: The project was founded through the Research Fund of the University of Antwerp (BOF).

Financial interests: The authors have no relevant financial interest to disclose.

Non-financial interests: Author XX serve on advisory board of Company Y but receives no compensation this role.

Ethics approval: The University of Antwerp Research Ethics Committee has confirmed that no ethical approval is required.

Consent to participate: Not applicable

Consent for publication: All authors have read and agreed to the published version of the manuscript.

Availability of data and materials: No data was utilized in this study.

Code availability: All the code utilized in this research is available in the digital document located at: https://jriverspejo.github.io/paper2_manuscript/.

Authors' contributions: *Conceptualization:* S.G., S.D.M., T.vD., and J.M.R.E.; *Methodology:* S.D.M., T.vD., and J.M.R.E.; *Software:* J.M.R.E.; *Validation:* J.M.R.E.; *Formal Analysis:* J.M.R.E.; *Investigation:* J.M.R.E.; *Resources:* S.G., S.D.M., and T.vD.; *Data curation:* J.M.R.E.; *Writing - original draft:* J.M.R.E.; *Writing - review & editing:* S.G., S.D.M., and T.vD.; *Visualization:* J.M.R.E.; *Supervision:* S.G. and S.D.M.; *Project administration:* S.G. and S.D.M.; *Funding acquisition:* S.G. and S.D.M.

6. Appendix

6.1. Additional definitions

6.2. Why do we need to estimate judges' abilities?

References

- Agresti, A., 1992. Analysis of ordinal paired comparison data. *Journal of the Royal Statistical Society* 41, 287–297. URL: <https://www.jstor.org/stable/2347562>, doi:10.2307/2347562.
- Bartholomew, S., Nadelson, L., Goodridge, W., Reeve, E., 2018. Adaptive comparative judgment as a tool for assessing open-ended design problems and model eliciting activities. *Educational Assessment* 23, 85–101. doi:10.1080/10627197.2018.1444986.
- Bartholomew, S., Williams, P., 2020. Stem skill assessment: An application of adaptive comparative judgment, in: Anderson, J., Li, Y. (Eds.), *Integrated Approaches to STEM Education*. *Advances in STEM Education*. Springer, pp. 331–349. doi:10.1007/978-3-030-52229-2_18.
- Boonen, N., Kloots, H., Gillis, S., 2020. Rating the overall speech quality of hearing-impaired children by means of comparative judgements. *Journal of Communication Disorders* 83, 1675–1687. doi:10.1016/j.jcomdis.2019.105969.
- Bradley, R., Terry, M., 1952. Rank analysis of incomplete block designs: I. the method of paired comparisons. *Biometrika* 39, 324–345. URL: <http://www.jstor.com/stable/2334029>, doi:10.2307/2334029.
- Bramley, T., 2015. Investigating the reliability of adaptive comparative judgment. URL: <http://www.cambridgeassessment.org.uk/Images/232694-investigating-the-reliability-of-adaptive-comparative-judgment.pdf>. cambridge Assessment Research Report.
- Bramley, T., Vitello, S., 2019. The effect of adaptivity on the reliability coefficient in adaptive comparative judgement. *Assessment in Education: Principles, Policy and Practice* 71, 1–25. doi:10.1080/0969594X.2017.1418734.
- Counterfactual, 2024. Merriam-webster.com dictionary. URL: <https://www.merriam-webster.com/dictionary/hacker>. retrieved July 23, 2024.
- Crompvoets, E.A.V., Béguin, A.A., Sijtsma, K., 2022. On the bias and stability of the results of comparative judgment. *Frontiers in Education* 6. URL: [url{https://www.frontiersin.org/articles/10.3389/feduc.2021.788202}](https://www.frontiersin.org/articles/10.3389/feduc.2021.788202), doi:10.3389/feduc.2021.788202.
- Gijzen, M., van Daal, T., Lesterhuis, M., Gijbels, D., De Maeyer, S., 2021. The complexity of comparative judgments in assessing argumentative writing: An eye tracking study. *Frontiers in Education* 5. URL: [url{https://www.frontiersin.org/articles/10.3389/feduc.2020.582800}](https://www.frontiersin.org/articles/10.3389/feduc.2020.582800), doi:10.3389/feduc.2020.582800.
- Gross, J., Yellen, J., Anderson, M., 2018. *Graph Theory and Its Applications*. Textbooks in Mathematics, Chapman and Hall/CRC. doi:<https://doi.org/10.1201/9780429425134>. 3rd edition.
- Jones, I., 2015. The problem of assessing problem solving: can comparative judgement help? *Educational Studies in Mathematics* 89, 337–355. doi:10.1007/s10649-015-9607-1.
- Lesterhuis, M., 2018. The validity of comparative judgement for assessing text quality: An assessor’s perspective. Ph.D. thesis. University of Antwerp.
- Luce, R., 1959. On the possible psychophysical laws. *The Psychological Review* 66, 482–499. doi:10.1037/h0043178.
- Marshall, N., Shaw, K., Hunter, J., Jones, I., 2020. Assessment by comparative judgement: An application to secondary statistics and english in new zealand. *New Zealand Journal of Educational Studies* 55, 49–71. doi:10.1007/s40841-020-00163-3.
- McElreath, R., 2020. *Statistical Rethinking: A Bayesian Course with Examples in R and STAN*. Chapman and Hall/CRC.
- Neal, B., 2020. Introduction to causal inference from a machine learning perspective. URL: https://www.bradyn Neal.com/Introduction_to_Causal_Inference-Dec17_2020-Neal.pdf. last accessed 30 April 2024.
- Neyman, J., 1923. On the application of probability theory to agricultural experiments. essay on principles. section 9. *Statistical Science* 5, 465–472. URL: <http://www.jstor.org/stable/2245382>. translated by Dabrowska, D. and Speed, T. (1990).
- Pearl, J., 2009. *Causality: Models, Reasoning and Inference*. Cambridge University Press.
- Pearl, J., 2010. An introduction to causal inference. *The international journal of biostatistics* 6, 855–859. URL: <https://www.degruyter.com/document/doi/10.2202/1557-4679.1203/html>, doi:10.2202/1557-4679.1203.
- Pearl, J., Glymour, M., Jewell, N., 2016. *Causal Inference in Statistics: A Primer*. John Wiley & Sons, Inc.
- Pearl, J., Mackenzie, D., 2018. *The Book of Why: The New Science of Cause and Effect*. 1st ed., Basic Books, Inc.
- Plackett, R., 1975. The analysis of permutations. *Journal of the Royal Statistical Society* 24, 193–202. URL: <https://www.jstor.org/stable/2346567>, doi:10.2307/2346567.

- Pollitt, A., 2012a. Comparative judgement for assessment. *International Journal of Technology and Design Education* 22, 157—170. doi:[10.1007/s10798-011-9189-x](https://doi.org/10.1007/s10798-011-9189-x).
- Pollitt, A., 2012b. The method of adaptive comparative judgement. *Assessment in Education: Principles, Policy and Practice* 19, 281—300. doi:[10.1080/0969594X.2012.665354](https://doi.org/10.1080/0969594X.2012.665354).
- Rubin, D., 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology* 66, 688—701. doi:[10.1037/h0037350](https://doi.org/10.1037/h0037350).
- Shaughnessy, J., Zechmeister, E., Zechmeister, J., 2010. *Research Methods in Psychology*. McGraw-Hill. URL: https://web.archive.org/web/20141015135541/http://www.mhhe.com/socscience/psychology/shaugh/ch01_concepts.html. retrieved July 23, 2024.
- Thurstone, L., 1927. A law of comparative judgment. *Psychological Review* 34, 482—499. doi:[10.1037/h0070288](https://doi.org/10.1037/h0070288).
- Tutz, G., 1986. Bradley-terry-luce model with an ordered response. *Journal of Mathematical Psychology* 30, 306—316. doi:[10.1016/0022-2496\(86\)90034-9](https://doi.org/10.1016/0022-2496(86)90034-9).
- van Daal, T., 2020. Making a choice is not easy?!: Unravelling the task difficulty of comparative judgement to assess student work. Ph.D. thesis. University of Antwerp.
- van Daal, T., Lesterhuis, M., Coertjens, L., Donche, V., De Maeyer, S., 2019. Validity of comparative judgement to assess academic writing: examining implications of its holistic character and building on a shared consensus. *Assessment in Education: Principles, Policy & Practice* 26, 59—74. doi:[10.1080/0969594X.2016.1253542](https://doi.org/10.1080/0969594X.2016.1253542).
- van Daal, T., Lesterhuis, M., Coertjens, L., van de Kamp, M., Donche, V., De Maeyer, S., 2017. The complexity of assessing student work using comparative judgment: The moderating role of decision accuracy. *Frontiers in Education* 2. URL: <https://www.frontiersin.org/articles/10.3389/feduc.2017.00044>, doi:[10.3389/feduc.2017.00044](https://doi.org/10.3389/feduc.2017.00044).
- Verhavert, S., Bouwer, R., Donche, V., De Maeyer, S., 2019. A meta-analysis on the reliability of comparative judgement. *Assessment in Education: Principles, Policy and Practice* 26, 541—562. doi:[10.1080/0969594X.2019.1602027](https://doi.org/10.1080/0969594X.2019.1602027).
- Wright, S., 1927. Correlation and causation. *Correlation and causation* 20, 557—585. URL: https://books.google.co.ao/books/about/Journal_of_Agricultural_Research.html?hl=pt-PT&id=INNdIV_qpwlC.