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Investigating lived ostracism: valid causal inference requires articulating the causal estimand

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ABSTRACT
The field of ostracism research is witnessing a growing interest in understanding ostracism – being excluded and ignored – as a lived experience outside of the laboratory context. How do researchers draw valid causal conclusions about naturally occurring experiences of ostracism without relying on experimental designs? In this article, we draw on insights from the well-established causal inference framework to emphasize a critical step for strengthening causal rigor: stating the causal estimand. Using an intuitive example, we illustrate what a causal estimand is, how to define it, and why it matters. With this article, we encourage readers to think clearly about causal estimands before conducting any data analysis. This conceptual step holds the potential for enhancing the rigor and precision of research studying ostracism as a naturally occurring phenomenon.

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The field of ostracism research has witnessed a shift in its primary focus on experimentally created experiences of ostracism (e.g., being ignored and excluded in Cyberball, a virtual ball-tossing game; Hartgerink et al., 2015; Williams & Jarvis, 2006) to lived experiences of ostracism that naturally occurred in people's lives. To investigate the lived experience of ostracism, scholars are increasingly adopting research designs beyond lab experiments, such as cross-sectional data, longitudinal surveys, and ecological momentary assessments e.g., (Büttner et al. 2024; Marinucci et al. 2023; Nezlek et al. 2012; Ren and Evans 2021; Riva et al. 2017; Stavrova et al. 2022). There are many reasons why lived ostracism is gaining increasing research attention. Studying lived ostracism not only offers a valuable opportunity to test existing theories and develop new ones in ecological settings but also holds significant societal relevance. Scientific knowledge about lived ostracism can offer critical insights into effectively addressing ostracism and its impacts, informing policies designed to promote positive social change and enhance social inclusion.

Studying lived ostracism is important. But a core challenge emerges: how do scholars draw valid causal conclusions without experimental designs? Here, we put forth that, as a first step, scholars should conceptually define their causal effect of interest before conducting any data analysis (Rubin, 2007). The causal effect of interest is the causal quantity scholars aim or seek to estimate; known as the "causal effect estimand" (Rubin, 1974, 1990; Splawa-Neyman et al., 1990). To illustrate its relevance, consider making bread. To make a successful loaf of bread, one of the first steps is to decide what to make – whether it is multigrain, sourdough, or a fluffy sweet loaf. If we don't decide what we are aiming for and simply follow a default recipe, we are likely to end up with a loaf that we didn't want in the first place. Our proposition here follows the same logic: Just like making bread, answering a causal question requires careful thought and planning. Before we begin, we need to decide what we are trying to make – in more formal language, what the causal estimand is. Without defining the causal estimand,

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we may end up following a statistical procedure that does not answer our causal question. This mismatch can lead to misinterpretations of statistical results, and ultimately, wrong conclusions.

In the next section, we further illustrate what a causal estimand is, and why it is important to define it, using a hypothetical running example of lived ostracism. This example is designed to provide an intuitive understanding of causal estimands and their implications for research. For those seeking to implement the recommendation in practice, we also highlight accessible tutorials that we have written specifically for psychologists.

Introducing a running example

The example builds on one of our own research programs in which we seek to understand how ostracism perpetuates itself. Before this line of work, a widely accepted conclusion in the field was that ostracism would lead to one of two behavioral responses. As an early version of the Williams's need threat model noted, ostracized individuals either "toe the line" (prosocial behavior) to regain inclusion or "lash out" (antisocial behavior) to regain control (Williams, 2009). Decades of empirical studies supported these two behavioral responses (e.g., Maner et al., 2007; Ren et al., 2018; Sommer & Bernieri, 2014). In a series of experiments, together with Dr Williams and colleagues, we uncovered a third response to ostracism – solitude seeking (Ren et al., 2016, 2021). Ironically, this very response to ostracism (solitude seeking) signals actors' low social interest, putting them at risk for future ostracism (Ren & Evans, 2021). This vicious cycle suggests that ostracism may trigger a downward spiral into social isolation over time (Ren & Evans, 2021; Ren et al., 2016, 2021).

Now, suppose our research team is putting the causal link (ostracism – > solitude seeking) to the test in naturalistic settings. Our target population is the adult population (18 years of age and over) in a specified nation. Our research interest is in understanding the causal effect of lived ostracism on solitude seeking within this population. Specifically, based on our previous work as reviewed above, we expect that reducing ostracism in the nation leads to less solitude seeking (our hypothesis).

What exactly is the causal effect of lived ostracism?

Although the causal estimand is rarely defined in the current research practice, the causal effect that is implicitly adopted in the field (i.e., the default causal estimand) is – using the language of the causal inference framework – the "average treatment effect" (ATE; Rubin, 1974). To understand ATE, consider the following thought experiment with two parallel universes. Imagine a middle-aged man, David, who is an individual in our target population. In Universe A, David is socially included (or not ostracized). Here, he rarely seeks solitude (outcome of interest), scoring only a 2.5 on a 1–5 solitude seeking scale (with 1 being never seeking solitude, and 5 being constantly seeking solitude). Conversely, in Universe B, David faces ostracism, resulting in frequent solitude seeking behavior, scoring as high as a 4.0 on the same scale. Now, David's individual causal effect can then be readily defined as the difference in his outcomes between the two universes (i.e., 4.0–2.5 = 1.5, on the 5 point scale). Let us do this mental exercise for all individuals in the population and record all individual causal effects in a column. Averaging across all individual causal effects in the column produces the ATE of ostracism on solitude seeking. Using more formal language, ATE is defined as the difference in average potential outcomes between a scenario where everyone is exposed to ostracism (Universe B) and another scenario where everyone is unexposed (Universe A).[1] This effect (ATE) is routinely – albeit implicitly – adopted as the causal estimand in ostracism research and psychological research broadly.

To further illustrate this, we now present a numerical example in Table 1. For ease of understanding, suppose we have eight individuals in our population. Each individual in the population has two potential outcomes: one in Universe A, and the other in Universe B. Each individual's causal effect is calculated by subtracting the outcome in Universe A from the outcome in Universe B. As the table

Table 1. A hypothetical numerical example illustrating the average treatment effect (ATE) and the effect of treatment on the treated (ETT).

Population	Y in Universe A (all included)	Y in Universe B (all ostracized)	Individual causal effect	Reality (lived experienced)
Person 1 (David)	2.50	4.00	1.50	ostracized
Person 2	2.00	2.90	0.90	ostracized
Person 3	2.10	3.90	1.80	ostracized
Person 4	1.50	1.20	−0.30	included
Person 5	1.90	1.30	−0.60	included
Person 6	2.20	2.40	0.20	included
Person 7	2.70	1.10	−1.60	included
Person 8	2.90	1.40	−1.50	included
Average in the entire population (persons 1–8)	2.23	2.28	**0.05**	**Average Treatment Effect, ATE**
Average in the ostracized subset (persons 1–3)	2.20	3.60	**1.40**	**Effect of Treatment on the Treated, ETT**

Note. In the hypothetical numerical example, we are interested in testing whether reducing ostracism (a binary exposure: being ostracized vs. included) decreases solitude seeking behavior (Y; measured on a 1–5 point scale, with 1 = never seeking solitude; 5 = constantly seeking solitude). For each individual, the observed outcome is underlined; the counterfactual outcome is unobservable in reality.

shows, the average causal effect of ostracism on solitude seeking (i.e., ATE) is 0.05. This indicates that the effect of ostracism has a minimal impact on solitude seeking behavior in real life (i.e., only 0.05 on a 5-point scale). Based on this finding, we can conclude that reducing ostracism is unlikely to decrease solitude seeking in the target population.

Now, is our conclusion valid? No. We will explain why in the next section.

ATE may not be the effect we are interested in

ATE is only one way to conceptualize causal effects. ATE is relevant in experimental settings where participants are either randomly assigned to be ostracized or included. In such settings, it makes sense to compare outcomes between a universe where everyone was ostracized versus a universe where everyone was included. However, this difference is less meaningful to interpret in the context of lived ostracism experiences. A key challenge is that ATE requires comparing hypothetical, contrived universes, neither of which represents reality, while ignoring people's actual experiences (Loh & Ren, 2024a, 2024b). Because we are interested in learning about whether or not *reducing* lived ostracism would impact solitude seeking (as stated in our hypothesis), our causal interest is, in fact, whether solitary behaviors would change, if people's lived ostracism experiences were reduced from the status quo (i.e., reality). Therefore, instead of comparing two contrived universes, it is more meaningful to compare the reality with an ideal world of inclusion, Universe A (everyone included). This comparison does not concern those who are already included in reality (no change for them); but it concerns those who experience ostracism in real life – the ostracized subpopulation.

To continue with our numerical example, let us assume three out of eight individuals in Table 1 (persons 1–3) were exposed to ostracism in real life, while the other five (persons 4–8 in Table 1) were unexposed. This information is indicated in the last column of Table 1. Because our research interest is in the persons who were ostracized in real life – the ostracized subset of the population, we only need to focus on the first three rows of the table (persons 1–3). The causal effect can then be defined as the changes in solitude seeking behavior, if those who experienced ostracism in real life were unexposed to ostracism instead. This can be calculated as the average treatment effects among persons 1–3 by contrasting the reality with Universe A among this subset.

As Table 1 shows, the average effect among the ostracized subset of the population (i.e., the average of the individual causal effects among persons 1–3) is 1.40. This causal quantity is referred to as the effect of treatment on the treated (ETT) in the causal inference literature (Heckman & Robb, 1985); for an accessible introduction to ETT for psychologists, please see Loh and Ren (2024a). ETT informs us about the potential changes in the outcome of interest (i.e., solitude seeking behavior) if individuals who experience lived ostracism in real life were included instead. Specifically, we can expect a 1.40 decrease in solitude seeking in the ostracized subpopulation, if the ostracized subpopulation were included. Thus, contrary to the conclusion we drew earlier using ATE, this quantity informs us that ostracism does have a substantial impact on solitude seeking: reducing ostracism is likely to decrease solitary behaviors in the target population.

Additional options for defining the causal effect of ostracism

So far, we have offered a conceptual introduction to ETT as an alternative causal estimand to ATE. There are other causal estimands that could be relevant for ostracism research. Here, we briefly describe two methods that allow for quantifying the causal estimand that we consider particularly important for advancing the field: Robins's g-methods (Hernán & Robins, 2020) and Kennedy's Incremental Propensity Score (Kennedy, 2019).

The effect of ostracism over time

Ostracism may occur as a single, isolated event; however, it often happens repeatedly over time. How does the impact of ostracism unfold over time? What causal effects should we examine in a longitudinal setting? In contrast to the prevailing belief that longitudinal designs ease establishing causality compared to cross-sectional data, causal inference in longitudinal designs can be far from straightforward and potentially even more challenging (Loh & Ren, 2023c). When ostracism happens repeatedly over time, many intricate longitudinal effects can be of substantive interest. For example, in a simple longitudinal study with three time points, we may be interested in the lag one effect of ostracism at time 1 on solitude seeking at time 2, the lag one effect of ostracism at time 2 on solitude seeking at time 3 (note, these two effects need not be the same), and/or the lag two effect of ostracism at time 1 on solitude seeking at time 3. Only by clearly articulating the causal estimand can we examine how the impact of ostracism may unfold over time. To address the challenges of quantifying time-varying effects of longitudinal ostracism, readers may consider adopting Robins's g-methods (Hernán & Robins, 2020), including g-estimation (for tutorials, please see: Loh & Ren, 2023a, 2023b) and g-formula (for tutorials, please see Loh & Jorgensen, 2025; Loh et al., 2024). Both are well-established methods for quantifying and estimating time-varying causal effects in the presence of treatment-confounder feedback.

Insights for developing interventions

Scholars may be interested in causal insights that can motivate the development of anti-ostracism interventions. Because it is unrealistic to eliminate ostracism entirely, a more feasible alternative approach is to conceptualize each individual's chances of being exposed to ostracism (i.e., the propensity of being ostracized) along a continuum. We can then estimate the effect of reducing each individual's chances of being ostracized (e.g., through interventions). Under this approach, the causal effect in our running example would be rephrased as: how would solitary behaviors change on average if individuals' chances of being ostracized were merely reduced (without being eliminated)? This causal question challenges conventional conceptualizations of causal effects because it refers to partial (rather than complete) reductions in ostracism, which more closely aligns with real-world interventions. This is precisely what the Incremental Propensity Score (IPS) framework enables (Kennedy, 2019); for a tutorial, see (Loh & Ren, 2024b). Instead of interpreting a causal effect as a singular difference between everyone versus no one being ostracized (i.e., ATE), IPS interprets causal effects as the extent to which average outcomes change when the individuals' chances of being ostracized are incrementally nudged downward. This approach has the additional advantage of allowing scholars to derive policy-relevant causal estimates of how even small, partial changes in the odds of ostracism might already mitigate its overall negative consequences.

Conclusion

With this brief review article, we aim to foster an intuitive understanding of the "causal estimand" among ostracism scholars and highlight the importance of clearly defining it in research practice. As illustrated above, conceptualizing the causal estimand is a necessary first step in causal investigations. This step is particularly important as the field of ostracism research is moving to address causal questions in naturalistic settings. Without explicating the causal estimand (what we want to know), routine data-analytic methods tend to default to estimating ATE, like following a standard recipe for one kind of bread. But this "default loaf" may miss the mark when it comes to capturing the practically meaningful causal effects of lived ostracism – the other kinds of bread we actually care about. We hope this nontechnical material helps ostracism scholars develop a clear conceptual understanding of what ATE is, why it may not address their specific research questions, and what alternative approaches are available.

Thinking clearly about the causal estimand is particularly useful for addressing causal questions that are difficult to study in laboratory settings. For example, chronic ostracism (the "resignation stage" in Williams's model) remains understudied for exceptions, see (Marinucci et al., 2023; Riva et al., 2017; Rudert et al., 2021). According to Williams's model, chronic ostracism leads to feelings of alienation, unworthiness, helplessness, and depression (Williams, 2009). Investigating these effects requires estimating the causal impact of chronic ostracism as it occurs outside controlled environments. Without a principled causal approach, there is a risk of misinterpreting spurious correlations as causal effects and reaching erroneous conclusions.

Although our running example focused on the impact of ostracism, the recommended practice of specifying the causal estimand before any data analysis applies broadly to any causal research. For example, scholars might investigate the underlying mechanisms of ostracism's impact (i.e., causal mediation analysis; e.g., Ren et al., 2023), factors that increase or reduce the chances of being ostracized (e.g., Rudert et al., 2020), reasons why people choose to ostracize others (e.g., Ren & Evans, 2021; Wesselmann et al., 2012), the effectiveness of belonging-enhancing interventions (e.g., socializing; Stavrova & Ren, 2023), or the effects of social inclusion or contact as the flip-side of social exclusion (e.g., Ren, Stavrova, et al., 2022; Stavrova & Ren, 2021; Voelkel et al., 2021). Like the hypothetical running example, these inquiries benefit from starting with a precise causal estimand.

Before we conclude, we wish to emphasize that a precise causal estimand is only a first step. Valid causal inference requires a systematic, principled approach with other considerations (e.g., Dang et al., 2023; Poppe et al., 2025; Ren & Loh, 2024). To facilitate the adoption of causal inference methods, we briefly propose two recommendations. First, we advocate for team science (Dang et al., 2023) between substantive experts (e.g., ostracism researchers) and causal inference experts. Second, graduate programs or organizations may consider incorporating causal inference as a dedicated course in their psychology curricula; see, e.g. (Loh, 2023), for a causal inference workshop at an annual convention of the Society for Personality and Social Psychology. With growing interest and collective effort, we are optimistic that causal inference will become more widely adopted in practice. Our hope is that, by using the causal framework in future investigations, the field of ostracism research and psychological science broadly can achieve a more accurate understanding of naturally occurring exposures, build stronger theories, and inform policies and interventions with greater confidence and precision.

Note

1. While the fundamental problem of causal inference precludes observing both potential outcomes for the same individual, under certain assumptions, we can essentially impute each individual's hidden potential outcome (specifically what would have been counterfactually observed had they been assigned to the different condition) to estimate the ATE. An accessible review of these assumptions is offered in Loh and Kim (2023).

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Suggested Readings

Loh, W. W., & Ren, D. (2024a). Enhancing causal pursuits in organizational science: Targeting the effect of treatment on the treated in research on vulnerable populations. *Organizational Research Methods*, 10944281241246772. https://doi.org/10.1177/10944281241246772

An innovative proposal promoting the use of ETT for organizational and social sciences researchers.

Loh, W. W., & Ren, D. (2024b). The incremental propensity score approach for diversity science. *Advances in Methods and Practices in Psychological Science*, *7*(2), 25152459241240680. https://doi.org/10.1177/25152459241240681.

An accessible introduction to Kennedy's IPS for psychologists.

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The first tutorial introducing Robins's renowned g-estimation for psychologists and an implementation using lavaan.

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