The So-Called Influence Relationship is Questionable: Comments on Wen Zhonglin et al. (2024) [open review]

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Date: 2025-03-03T00:00:00+00:00

Abstract

Wen Zhonglin et al. (2024) published a paper in Acta Psychologica Sinica focusing on the long-standing ambiguous usage of the term "influence" and proposed the concept of "influence relationship," which may alter subsequent pragmatic practices within the Chinese-speaking psychological community. However, this article contains several points of contention: the term "influence," irrespective of language (Chinese or English) or audience (lay public or academic community), is universally regarded as causal language, and it is difficult to accept the authors' claim that it does not convey causal implications; "influence relationship" lacks a clear definition and appears to have no essential difference from causal relationship; the confusion between ends and means—whereby a third construct distinct from both causal and correlational relationships is created because the methodological approach cannot provide causal evidence for causal ends—is questionable. More importantly, the covariational and directional relationship between variables is not unnamed as the authors suggest; it has consistently been termed "prediction" in the academic literature. Accordingly, this commentary aims to remind academic colleagues to consider alternative approaches to describing such scenarios and to make prudent decisions regarding the introduction of the so-called "influence relationship" into research.

Full Text

Preamble

The So-Called Influence Relationship Requires Caution: A Commentary on Wen et al. (2024)

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Abstract

Wen et al. (2024) recently published a paper in *Acta Psychologica Sinica* that focused on the long-standing ambiguous usage of the term "influence" in Chinese psychology and proposed the concept of "influence relationship," which may alter subsequent linguistic practices in Chinese psychological research. However, several doubts remain regarding this proposal. First, the term "influence," in both Chinese and English and among both the general public and academics, is universally understood as causal language, making it difficult to accept the authors' argument that it does not convey causal meaning. Second, the "influence relationship" lacks a clear definition and appears to have no essential difference from causal relationships. Third, the paper confuses research goals with the means to achieve them, creating a strange third objective distinct from both causal and correlational relationships simply because the methodological means cannot provide causal evidence for a causal goal. More importantly, covarying relationships with directionality are not unnamed as the authors claim; they have long been called "prediction" in academia. This commentary aims to remind colleagues to consider alternative ways of describing such situations and to make prudent decisions about whether to introduce the so-called "influence relationship" into research.

Keywords: influence relationship, correlation relationship, causal relationship, influence factor, predictive research

Wen et al. (2024) published a paper in *Acta Psychologica Sinica* that constructively addressed the ambiguous usage of the term "influence" in psychology and creatively proposed the novel concept of "influence relationship," which is thought-provoking. However, this matter is significant as it may change the linguistic practices of Chinese psychology, necessitating careful consideration. Upon detailed reading, several doubts emerge, prompting this commentary for discussion with the original authors and academic colleagues.

1 Doubts About the Paper

Wen et al. (2024) argue that distinguishing among influence relationships, causal relationships, and correlational relationships is necessary, as misunderstanding influence relationships for the latter two can have serious consequences, yet the concept remains undefined. They propose that a correlational relationship satisfies the criterion of "covariation between cause and effect," an influence relationship further satisfies the criterion of "the cause occurring before the effect (directionality)," and a causal relationship satisfies both criteria plus "ruling out alternative explanations other than causal connection." For example, they suggest that if researchers in a cross-sectional study ask students to report their emotions and GPA, they can describe a significant regression coefficient as "emotion influences GPA" without ruling out any alternative explanations. Below, I elaborate on four doubts: from the perspective of essential elements for a conceptual article, the paper lacks a clear definition of "influence relationship";

conceptually, the proposed inference criteria cannot effectively distinguish influence relationships from causal relationships; in terms of meaning conveyed to readers, the term "influence" is universally regarded as causal language, making it difficult to convince readers that it does not convey causal meaning; and most importantly, the paper confuses goals with the means to achieve them.

1.1 What Kind of Relationship Is the So-Called Influence Relationship?

The most obvious doubt is that the "influence relationship" lacks a clear definition. Since the authors aim to propose a new concept distinct from correlational and causal relationships, they should at least clarify what the old concepts mean and what the new concept means, enabling readers to compare the three. However, throughout the paper, the authors only mention inference criteria (i.e., covariation + directionality) but never define correlational, influence, or causal relationships. This is unlikely an oversight, as the published reviewer comments show that Reviewer 1's Comment 2 and Reviewer 2's Comment 1 both pointed out the conceptual definition issue, yet the authors responded with inference criteria (directional correlational relationship) rather than definitions, even though they called these criteria definitions in the abstract.

Why can inference criteria not be treated as definitions? A ready case is causal relationships. Since Wen et al. (2024) "define influence relationship as a directional correlational relationship" in the abstract, causal relationships could similarly be defined as a directional correlational relationship that also rules out alternative explanations other than causal connection. The question then becomes: what "alternative explanations" need to be ruled out to infer causality? Various explanations are possible for the relationship between X and Y, one of which fits the definition of causality while others do not. Therefore, any explanation that makes the X-Y relationship not fit the definition of causality must be ruled out. So, what is the definition of a causal relationship? It appears that the "definition" of causality is a relationship that rules out all explanations that would prevent it from being a causal relationship. This awkward circularity suggests that inference criteria cannot substitute for definitions. Only with a clear definition can readers judge whether the proposed inference criteria appropriately serve to infer influence relationships; otherwise, after reading the entire paper, readers still won't understand what influence relationships are about. Moreover, while definitions may be disputed, they should have broad consensus; inference criteria may have commonly accepted standards but remain largely open and subordinate to definitions. For instance, the three criteria for inferring causal relationships pointed out by the authors are not the only discriminative standards, though commonly used (e.g., Pirlott and MacKinnon (2016) enumerated many causal inference criteria beyond these three).

Consider Bailey et al.'s (2024) definition: a causal effect refers to the hypothetical difference in variable Y under different conditions of intervention X for a population, part of a population, or an individual. Intervention refers to any intentional change to one or more variables in a model (often with the goal of revealing causal effects). Rubin (2005) offered a similar definition. In short, if changing X is hypothesized to make Y different, then X and Y are constructed as a causal relationship. Now examine Wen et al.'s (2024) understanding of influence relationships: for example, "but when it comes to influence, the usual understanding is that one event acts on another event, which is directional." Since one event has already acted on another, and "acting" necessarily means some change occurred in the second event, how is this relationship different from a causal relationship? Another example revealing the authors' understanding is their discussion of risk and protective factors, where they note the latter "can be simply understood as influence factors that reduce the probability of negative outcomes." Since a factor can already reduce the probability of an outcome variable, how is this relationship different from a causal relationship? Without a clear definition of influence relationship that differs essentially from causal relationship, the distinction seems untenable.

1.2 Is the So-Called Influence Relationship Really Different from Causal Relationship?

Of course, despite lacking a definition, Wen et al. (2024) do express how to distinguish causal from influence relationships. They propose that the fundamental difference lies in whether to follow the third inference criterion, which states that alternative explanations other than causal connection should be ruled out. Therefore, if they are not ruled out, it belongs to influence relationship. As previously mentioned, this criterion is largely a "catch-all provision" that can accommodate many more specific requirements (any explanation that makes the X-Y relationship not fit the definition of causality must be ruled out) and varies by research question. Most centrally, it aims to prevent "non-causal" covariation caused by reverse causality or third variables (Pirlott & MacKinnon, 2016).

This does not mean reverse causality or third variables are not allowed. For example, some X-Y relationships have been proven to be mutually causal (e.g., Tam & Inzlicht, 2024), but researchers worry that the observed covariation is entirely due to these confounds.

Consider an example: I want to know whether advertising investment during the pre-heating period before Double Eleven (Singles' Day) affects sales during Double Eleven—a common question for marketing practitioners. Clearly, the two have directionality in time (both conceptually and in measurement); regression would also reveal covariation—more advertising investment leads to more sales. However, imagine an extreme scenario: one day a platform suddenly has a system failure that charges advertising fees but doesn't actually deliver any ads to consumers. Worse still, even in this extreme case, covariation can still be observed—large merchants and big brands have bigger marketing budgets and higher sales targets, so naturally they invest more in advertising; even without ads, they would undoubtedly achieve larger sales than small merchants during the promotion period. The data researcher reports to the boss: advertising investment influences sales. The boss angrily responds: I just heard from the technical department's post-mortem that no ads were actually delivered! What kind of "influence" is this analysis showing? Fortunately (or unfortunately), most research questions don't have a technical department warning researchers that influence is impossible; humans must rely on limited research methods for inference. Bartram et al. (2024) offer an interesting example: height influences vocabulary. To satisfy the "directionality" requirement, we can modify this example to: height influences vocabulary one year later. According to Wen et al.'s (2024) "definition," proving this "influence" would be very easy—just include both newborns and young adults in the same sample, and with covariation and directionality but no need to rule out alternative explanations, a conclusion can be drawn. Allowing researchers to describe such results as "height influences vocabulary one year later" is problematic.

These examples convey that Wen et al. (2024) misunderstand the three criteria for causal inference as being independent, when they are far from it. If alternative explanations are not ruled out (e.g., business scale may simultaneously influence pre-promotion advertising investment and mid-promotion sales; age may simultaneously influence height and vocabulary), then the so-called directionality of the second criterion cannot be proven, and the "influence relationship" cannot be established. If alternative explanations are ruled out, then the difference between influence and causal relationships disappears. While methods for ruling out alternative explanations vary in quality, the third criterion itself cannot bear the weight of distinguishing influence relationships from causal relationships.

1.3 Can Readers Believe That "Influence" Does Not Denote Causal Relationship?

The ambiguous boundary between causal and influence relationships may stem from failing to grasp the meaning of the word "influence." The *Modern Chinese Dictionary* defines the verb "influence" as "to have an effect on others' thoughts or actions." Wen et al. (2024) identified English equivalents: impact, affect, influence. Merriam-Webster's primary definitions are: for *impact*, "to have a direct effect or impact on"; for *affect*, "to produce an effect upon (someone or something)" and "to act on and cause a change in (someone or something)"; for *influence*, "to affect or alter by indirect or intangible means" and "to have an effect on the condition or development of." All these definitions use explicit causal language (cause and effect).

Not only the general public but also academic researchers share this understanding. Haber et al. (2022) asked 47 PhDs, postdocs, and faculty in epidemiology, statistics, medicine, economics, and psychology to rate the causal implications of various academic expressions (none, weak, moderate, strong). Visual inspection of bar charts shows that while *cause* has the strongest causal implication (about 100% moderate or strong), *affect*, *impact*, and *influence* are not far behind (about 90%). The Dutch journal *Social Indicators Research* explicitly lists "influence" as "language that can only have a causal meaning" in its editorial, warning contributors that using such rhetorical strategies in (simple) cross-sectional studies will damage manuscripts (Bartram et al., 2024). Unfortunately, Wen et al. (2024) did not disclose these potential negative consequences for researchers' submissions and publications to those who might adopt their suggestions.

Thus, Wen et al. (2024) attempt to convince general readers and academic colleagues that "influence" does not convey causal meaning—a challenging goal that violates the original meaning of the word. Even if a concept other than causal and correlational relationships truly exists, "influence relationship" is not an appropriate name for this new concept.

1.4 Failure to Rule Out Alternative Explanations: Is It a Unique Variable Relationship Goal or Merely a Methodological Compromise?

Most importantly (the essential source of all doubts): the paper confuses goals with the means to achieve them. In terms of goals, the distinction is simply whether researchers aim to investigate causal relationships; for studies targeting causality, the evidence provided for causality can vary in strength (Hernán, 2018).

Wen et al. (2024) proposed the influence relationship because many studies aim to prove X influences Y in their goals but cannot provide strict causal evidence in their methods. Creating a third objective distinct from causal and correlational relationships for this reason is strange, because such studies essentially still hold causal goals. According to the definition of causal relationships, if a study's theoretical goal is "if X is changed, the researcher hypothesizes Y will be different," then the study targets causality, regardless of whether the researcher actually changes X or whether X can realistically be changed. Accordingly, many examples Wen et al. (2024) provide for influence relationships are, in terms of goals, causal relationships—e.g., teacher teaching quality influences student achievement. Researchers think: if teaching quality is changed, student achievement should differ; if results meet expectations, they might even suggest improving student achievement by enhancing teaching quality in the discussion—this is a causal issue. Whether researchers can rule out alternative explanations—the only difference Wen et al. (2024) propose between influence and causal relationships—is merely a methodological issue that does not change the researchers' underlying goal: regardless of means, they want to explain why student achievement varies, with teaching quality being one reason.

In fact, many studies that are not randomized experiments aim to answer causal questions: e.g., can reducing early morning university classes boost student GPA (Yeo et al., 2023); can embedding more plot reversals in movies achieve greater success (Knight et al., 2024); can avoiding COVID-19 infection prevent increased risk of neuropsychiatric symptoms (Kim et al., 2024); can improving a family's socioeconomic status enhance grandchildren's personality traits (Martin & Donnellan, 2021); can activating social mobility and reducing class rigidity decrease local violent crime (Mann et al., 2024); can reducing local neoliberalism increase government and resident support for pandemic responses (Liu et al., 2024). Although none of these six cases experimentally manipulated X, and some Xs are difficult to change by human will (let alone in research), these studies' theoretical constructions and practical concerns are undoubtedly causal—perhaps by changing X, good Y can be increased or bad Y avoided—this is where their significance lies. Arguing that researchers didn't aim to answer causal questions because they temporarily cannot provide sufficient evidence for causal goals puts the cart before the horse. Instead, most psychological empirical studies harbor causal goals, aiming to answer: why do people's psychology and behavior differ, and can changing certain factors improve them?

Although causally oriented, researchers often face practical constraints—whether X truly cannot be manipulated or insufficient funding/time supports experimental manipulation. Different studies provide causal evidence of varying strength through their means, which is difficult to categorize. Only at the methodological level is Wen et al.'s (2024) concept of a 0-1 continuous axis (which reviewers suggested deleting) appropriate: 1 represents empirical evidence that gives us complete confidence in causality, 0 represents no confidence (but seemingly cannot equate to correlational relationships). Many efforts can help a study move from 0 to 1, such as controlling variables, matching, regression discontinuity, instrumental variables, longitudinal tracking, cross-lagged models, within-between comparisons, direct testing of alternative explanations, difference-in-differences, Mendelian randomization, twin or sibling designs, naturalistic experiments, randomized experiments, etc. All make a study more persuasive for causal inference than simple non-experimental cross-sectional regression because they help rule out some alternative explanations that might challenge causality (e.g., reverse causality, comparing apples and oranges fallacy, third variables), though some strategies alone may still be close to 0 (e.g., simply using control variables hardly provides causal evidence). Randomized experiments are not permanently fixed at 1; in fact, factors like between-group heterogeneity, lack of measurement invariance across groups, gaps between theoretical concepts and actual manipulation, fat-hand interventions, interference, spillover, experimenter effects, etc., can all damage our confidence in causality (Bailey et al., 2024)—that is, make us doubt that changing X will change Y as researchers believe.

Clarifying goals and means also dispels Wen et al.'s (2024) concern about unmet prerequisites for mediation analysis. They argue that simply renaming some studies previously called correlational as influence relationships would allow these correlational studies to rightfully conduct mediation analysis without violating the essential requirement that mediation models are causal models. To this, we must borrow Hernán's (2018) title: "Scientific euphemisms do not improve causal inference from observational data." In fact, if a model is causal in its goals (and theoretical construction), mediation analysis is not hindered even if causal evidence cannot be temporarily provided in methods. Of course, authors need to acknowledge and readers need to note that causal goals may be largely unmet by methods, with many alternative explanations not ruled out—e.g., the dependent variable might influence the mediator. Conversely, if a model makes no theoretical sense as causality, changing its name ten times won't help; it cannot thereby satisfy the essential requirement that mediation models are causal models. Mediation analysis ultimately requires ruling out three possibilities: X's change does not cause the mediator's change, the mediator's change does not cause Y's change, and the mediator's effect on Y is independent of X's effect on Y (Ge, 2023). If X, though claimed to "influence" Y, is not a causal relationship such that changing X in any way would not change Y at all (at the theoretical, not statistical, level), then the two are "insulated"—where does mediation stand?

2 Another Possible Way of Description

Since covarying relationships with temporal directionality should not be called influence relationships, is there a name for them? Although Wen et al. (2024) repeatedly argue for the necessity of the term "influence relationship" and emphasize that such relationships are unnamed, in fact, they have always had a clear and well-established name—"prediction."

2.1 Goal Level

Hamaker et al. (2020) categorize scientific research into three types (not their original invention; similar classifications appear elsewhere): descriptive research; predictive research, which uses one or more temporally prior variables to predict values of a specific temporally later variable; and explanatory research, whose main goal is to understand underlying causal mechanisms and develop interventions. A few examples quickly illustrate why some researchers only care about predictive goals, not causal ones. Suppose I want to design a commercial medical insurance plan. The only information I have is each client's medical examination report, and I want to know how likely this client is to contract a disease covered by the policy after the insurance takes effect, so I can design premiums and coverage to avoid losses. As an insurance designer, my goal is obviously not to reduce the probability of claims by changing the client's health (X); I just want to know the probability. Similarly, public health research often puts many demographic indicators into models to calculate whether groups at certain levels of these indicators are more likely to develop certain diseases than others. If researchers find that certain gender, sexual orientation, or socioeconomic status groups have higher depression risk, they obviously cannot suggest these groups simply change their gender, orientation, or status. Instead, they prioritize education, guidance, or interventions for these groups given limited resources—and this intervention is not about changing X (gender, orientation, status). (Note: Not all studies using these variables as independent variables are predictive research; e.g., a study concerned with poverty alleviation—similar to changing socioeconomic status—to reduce mental illness risk is causal research, even without actual poverty alleviation, only measurement. The key is the researcher's actual concern, not the variables used as examples.) The most fashionable example of predictive research is probably artificial intelligence (whether predictive or generative). Although AI training models are far more complex than the linear and logistic prediction models commonly used in psychology, they share the same goal in terms of objectives: as an AI, I must fully learn probabilistic relationships in the training sample. I never worry about whether any X-Y pair has a causal relationship; my only effort is to guess which Y best meets the inputter's requirements when someone inputs some Xs that have no direct corresponding cases in my training sample.

In these examples, researchers have no interest in causal goals ("if X is changed, the researcher hypothesizes Y will be different"). They don't want to change X; they only want to know: if X is known, to what extent can Y be accurately predicted? Therefore, predictive researchers don't need to worry much about confounding from alternative explanations (Bailey et al., 2024). They only care about which predictors to add or remove, which quantification methods can improve prediction accuracy (Martin & Kushwaha, 2024), and how to select samples that help generalize relationships captured from training samples to broader populations and environments (or where the boundaries are). For instance, researchers use bank transaction records (reflecting human behavior) to predict personality traits (Gladstone et al., 2019), without worrying whether spending influences personality, personality influences spending, or a third variable influences both. As long as spending is known and personality can be guessed with acceptable accuracy, the predictive goal is achieved. Simply put, they don't worry that the sun rising in the east isn't universally true; as long as they don't leave Earth, they can guess where the sun will rise tomorrow. That is, as long as there are no fundamental differences in population and environmental characteristics between training samples and application scenarios, their accumulated knowledge enables effective predictions of Y. Now recall the earlier example: if the data researcher's analytical goal changes to using advertising investment to predict sales, we can easily believe that even without causality, this predictive conclusion can be effectively replicated in future years. Similarly, when you return home for the Lunar New Year and encounter a completely unfamiliar relative, you need to guess their vocabulary level to decide how to talk to them. You recall a study you conducted where height could predict vocabulary in a 0-30-year-old sample. Although no causality exists, this study is particularly useful at this moment: if height is under 1 meter, childlike language is most appropriate; if height is similar to yours, you can talk with your usual vocabulary without worrying they won't understand. But if you unfortunately encounter someone aged 30-60 and want to generalize the predictive conclusion from the 0-30 sample (taller height, larger vocabulary) to this person, the predictive validity becomes highly questionable. Some psychology researchers even call for more attention to predictive research and making explanation a secondary goal (Yarkoni & Westfall, 2017); of course, the choice should depend on the researcher's topic of interest.

2.2 Method Level

If a researcher has already chosen causality (rather than prediction) as the goal, but their theoretical arguments and empirical evidence can only show that X precedes Y and the two covary, unable to empirically rule out most alternative explanations threatening causality, then instead of calling it "X can influence Y" and then educating the public that this influence is not what they understand in daily life, why not directly call it "X can predict Y"? In fact, most researchers do exactly this (examples from top psychology journals include Cheng et al., 2023; Engstrom et al., 2024; Lu et al., 2021; Meyer et al., 2023; Rotella et al., 2021; Shen & Shoda, 2021; Stasi et al., 2024; Wright & Jackson, 2023). Using "predict" here does not mean the study is prediction-oriented; it merely provides a factual description of the analysis and its results. Lexically, the *Modern Chinese Dictionary* defines prediction as "to speculate or determine in advance," and Merriam-Webster defines *predict* as "to declare or indicate in advance." Without redefinition, general readers can grasp what researchers intend to convey.

2.3 Goals and Means

Here, I am not proposing a new concept beyond correlational relationships. On the contrary, whether aiming for predictive goals or indicating predictive results, these are undoubtedly non-causal. I represent these distinctions graphically in Figure 1 [Figure 1: see original paper]. At the goal level, the first distinction is whether researchers want to investigate causal relationships ("if X is changed, the researcher hypothesizes Y will be different"). If not, the study does not need to be evaluated by causal standards, with further distinctions based on directionality: if researchers care about direction, it's predictive research; if not, it's purely correlational research (simply calling it correlational relationship seems somewhat ambiguous). If researchers are committed to investigating causal relationships at the goal level, even if they cannot fully prove it in methods (even without actually manipulating X), the study should be evaluated by causal standards. If alternative explanations threatening causality can be largely ruled out in methods, readers have stronger confidence in the causal relationship (near the 1 end of the axis in Figure 1); if not, confidence is weaker (near the 0 end), and researchers should not simply claim causal conclusions (though they can discuss causal implications) but should describe results and conclusions using language not specific to causality: e.g., X is associated with Y (be associated with, association/relationship between/of … and/with …); the more … the more …; people with higher X have higher Y; one group has higher Y than another; X can predict Y (predict), etc.

3 Action Recommendations

Despite many doubts about the influence relationship argument, Wen et al. (2024) accurately identified a real problem in current research practice—the term "influence" is used confusingly, and studies with directionality but insufficient causal evidence face reporting dilemmas. The following recommendations (with accompanying references) are offered for authors, reviewers, and readers to consider.

First, clearly define research goals. (A) Purely correlational research: common examples include criterion validity analysis of personality questionnaires, e.g., researchers wanting to know how Junzi personality differs from the Big Five, which are parallel without temporal sequence (Ge et al., 2021); or marketing personnel conducting shopping basket analysis (association rule mining) to understand which products consumers are most likely to purchase together in one shopping trip (the classic case being beer and diapers), where which is bought first doesn't matter, allowing improvements in shelf placement and promotional strategies (Hahsler et al., 2005). (B) Predictive research: common examples include screening and prediction of high-risk groups for diseases, mental health issues, or risky behaviors (e.g., Chen et al., 2024; Hur et al., 2024), and admissions committees or employers using test scores, interview performance, resume data, or personality/mental health assessments to predict future academic or job performance. (C) Causal research (explanatory research): currently the main part of psychological empirical research, aiming to answer "why." The distinctions among goals are shown in Figure 1. If the goal is truly one of the first two, there's no need to evaluate research design quality from a causal perspective. However, it must be noted that studies whose essence is causal should not escape causal scrutiny by voluntarily downgrading to predictive research while explicitly or implicitly suggesting practical concerns about changing X to improve Y throughout the paper (Alvarez-Vargas et al., 2023; Bartram et al., 2024; Rohrer & Wenz, 2024). Causal research should not be considered psychology's only or superior goal, with non-causal research viewed with prejudice or disdain; the appropriate goal is what fits the research topic.

Second, for causal (explanatory) research, researchers should be allowed to discuss causal implications even without explicit causal evidence. Many articles make similar calls: for example, Hernán (2018) suggests that if the goal is causal research, use causal language to accurately describe research goals without hedging—using causal terms outside the results section may be appropriate, but faithfully describe results in the results section. Grosz et al. (2020) also suggest that non-experimental studies can openly discuss causal effects; similar discussions appear in Bailey et al. (2024) and Bartram et al. (2024). This is undoubtedly not a suggestion to overstate conclusions. On the contrary, only if researchers clearly define their causal goals can they admit the extent to which these goals are realized. A possible template might be: This article aims to investigate the causal relationship between income inequality and well-being (inequality influences well-being), empirically supporting their covariation, theoretically arguing their directionality, ruling out alternative explanations one through four (e.g., ruling out potential confounding by economic development stage, ensuring comparisons between income-equal and unequal areas don't merely reflect poor vs. wealthy areas…), but failing to rule out alternative explanations five through eight (e.g., some cultural value atmosphere might promote inequality while simultaneously harming well-being, or well-being perceptions might 反过来 influence local residents' tolerance for inequality…). These results give us considerable confidence in their causal relationship (increasing income equality can improve citizen well-being) or still cannot evaluate the causal relationship (only preliminarily suggesting possibility, awaiting future research).

Third, communicate non-causal results frankly. Many statements with directionality but not described as "influence relationships" that Wen et al. (2024) cite seem unproblematic—terms like association, relationship, linkage, predictable are clear and honest expressions. If researchers worry about indicating direction, simply adding "subsequent" or "several years later" before Y easily solves this concern. Another example they cite, "people from regions with higher ancestral diversity are more willing to publicly express emotions," seems like an excellent expression that honestly describes the observed fact itself. If researchers still worry that admitting the non-causal nature of their evidence might invite disdain, consider this pre-registered experiment: Alvarez-Vargas et al. (2023) had 142 psychology faculty, postdocs, and PhDs read abstracts; some read abstracts using causal language like impact, affect, cause, while others read abstracts using predict. Results showed that abstracts using predict were perceived by participants as having significantly higher research design and analysis quality than those using causal language. Therefore, even from a practical standpoint, researchers considering switching their non-causal results to "influence relationships" may need to think twice, as existing evidence doesn't seem to show they would benefit from it.

Fourth, causal evidence is not all-or-none. It is particularly inappropriate to believe that questionnaire data (or more broadly, observational data) are destined to be unable to provide causal information. Wen et al.'s (2024) statement that "psychology generally believes questionnaire-based research cannot study causal relationships between variables" seems ill-considered. As the long list of methods mentioned earlier shows, psychology and other discipline researchers are actively using various methods to capture information that can provide causal implications from non-experimental surveys (Bartram et al., 2024; Gianicolo et al., 2020; Hammerton & Munafò, 2021; Igelström et al., 2022; Pearl, 2009; Rohrer, 2018, 2024; Wang et al., 2023). In recent years, causal inference analytical techniques have developed in many disciplines; psychology researchers might consider looking beyond psychology to improve causal inference methods through broader methodological literature (External Reviewer 1 recommended related books; interested readers can refer to the published reviewer comments on the journal's website). These efforts may not directly move a causally-oriented study to the 1 end of the axis in Figure 1, but efforts from 0 to 0.2 or 0.4 to 0.6 can also contribute valuable insights. For example, Nonkovic et al. (2024) used a sibling design to examine the effects of maternal smoking during pregnancy, finding that: between children from different families (with large differences in genes and upbringing environments), DNA methylation differences were only 6%; in contrast, between different children within the same family (similar genes and environments but mothers' smoking behaviors differed during different pregnancies), DNA methylation differences were as high as 94%; and prenatal and postnatal secondhand smoke had no similar effects. Under the practical constraint that pregnant women cannot be randomly assigned to smoke, this observational data actually provides considerable causal information, though alternative explanations can still be proposed. Therefore, the contribution of research methods beyond randomized experiments to accumulating causal knowledge should not be dismissed with a simple "correlation does not imply causation."

Fifth, perhaps we should not expect a single study to provide conclusive answers to causal theories, even randomized experiments. As Grosz et al. (2020) emphasize with a seemingly circular statement—"causal inference is speculative inferences"—the belief that a single study's direct results can be immediately packaged as causal conclusions is unreasonable. Any research method only collects evidence for evaluating causal hypotheses, not causality itself. The causal effect triangulation framework states that three efforts should continuously synergize and cycle: improving hypotheses and theories, obtaining estimates from observational data, and measuring impacts through well-defined interventions (Bailey et al., 2024). Therefore, whether hinting at possible associations near the 0 end of the axis in Figure 1 or ruling out all alternative explanations imaginable by current theory near the 1 end, these are all processes toward causal goals. Only the accumulation of these efforts can make us increasingly confident in a causal proposition.

Wen et al. (2024) constructively placed the long-unresolved issue of "influence" usage in Chinese psychology under the spotlight, enabling more researchers to notice this problem and join the discussion. This commentary hopes to contribute a different perspective to this discussion, reminding colleagues to consider alternative ways of describing relevant situations and to make prudent decisions about whether to introduce the "influence relationship" concept proposed by Wen et al. (2024) into research.

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Note: Figure translations are in progress. See original paper for figures.