# Causal Claims in Contribution Analysis

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**Abstract:** *This article is a tribute to John Mayne's work on Contribution Analysis. It focuses on the causal claims Contribution Analysis aims to address, and on how these have evolved since the approach was first published by John in 1999. It first sets out four types of causality with relevance for Contribution Analysis: counterfactual, generative, INUS, and probabilistic causation. It then describes how John integrated the INUS condition and probabilistic elements into the Contribution Analysis approach, followed by how John's thinking evolved regarding the question of whether the approach could—and should—also address counterfactual questions. The article concludes with observations on how Contribution Analysis can flexibly integrate elements from different causality types.*

**Keywords:** *Contribution Analysis, causality, causal claims, counterfactual causation, generative causation, INUS, probabilistic causation, John Mayne*

**Résumé :** *Cet article est un hommage aux travaux de John Mayne sur l'analyse de contribution. Il traite des liens de causalité que l'analyse de contribution vise à examiner et de la façon dont ceux-ci ont évolué depuis la première publication de l'approche par John en 1999. Il énumère d'abord quatre types de causalité pertinents pour l'analyse de contribution : contrefactuelle, générative, INUS et probabiliste. Il décrit ensuite la façon dont John a intégré la condition INUS et les éléments probabilistes dans l'approche d'analyse de contribution, pour ensuite traiter de la façon dont les réflexions de John ont évolué quant à la question de savoir si l'approche pourrait—et devrait—aussi traiter les questions contrefactuelles. L'article se conclut avec des observations sur la façon dont l'analyse de contribution peut intégrer de façon flexible des éléments de différents types de causalité.*

**Mots clés :** *analyse de contribution, causalité, lien de causalité, causalité contrefactuelle, causalité générative, INUS, causalité probabiliste, John Mayne*

## INTRODUCTION

I met John for the first time in 2010 when I was trying to figure out what "cost-contribution analysis" could possibly mean; a concept I had found in a meta-evaluation (Eureval-C3E, 2006) I reviewed when researching aid efficiency

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(Palenberg, 2011). One of the authors of the meta-evaluation referred me to John and we scheduled an interview. With that interview, John and I began our more than decade-long collaboration and friendship. One of our favorite topics was what types of causal claims Contribution Analysis could reasonably make. This article summarizes some of these discussions and illustrates John's further thinking on the subject based on his rich publication record.

Methodologically, the article relies on desk review and chronological contextualization of publications on Contribution Analysis and on other subjects that influenced John's thinking, including a frequency analysis of key terms in selected articles. The article also draws on the author's interactions with John between 2010 and 2021.

After this introduction, the article is structured as follows. The next section introduces four accounts of causation with relevance for Contribution Analysis. The third section then describes the *generative* causal claims Contribution Analysis focuses on. The next two sections address linkages of Contribution Analysis to other types of causality: to INUS and probabilistic causality in the fifth section, and to counterfactual causality in the fifth section. The article concludes with summary observations.

## ACCOUNTS OF CAUSATION

Published literature on causation spans centuries. It is rich and diverse. It is also controversial in the sense that several competing philosophical accounts of causation coexist—each with its own understanding of cause and effect and an accompanying set of approaches for inferring them.

In what follows, I will briefly describe four accounts of causation: counterfactual, generative, INUS, and probabilistic causation. Each of these accounts—in its own way—influenced John's thinking on Contribution Analysis.

*Counterfactual causation* understands cause and effect by means of comparing the real world with a fictitious one in which the intervention does not exist. In this account, all further differences between these two worlds *are*—by definition—the effects caused by the intervention. The counterfactual account goes back to Lewis (1973, 1986).

Counterfactual causation is closely related to John's original motivation for developing Contribution Analysis. In its earliest publications on the topic, he introduced Contribution Analysis as a performance-measurement-based alternative to more rigorous evaluation approaches able to attribute observed change to an intervention. At that time, John pursued two objectives with Contribution Analysis. The first was to obtain a credible picture of the results that could be attributed to an intervention, in instances when more rigorous evaluation approaches capable of doing this could not be applied (Mayne, 1999). Hence, originally, John considered Contribution Analysis as an alternative approach for inferring counterfactual causality. However, as described further below, John later moved away from this proposition when further developing the Contribution

Analysis approach. The second purpose was to increase understanding of how and why an intervention had contributed to results, reflecting another type of causality: *generative causation*. As described later, John developed Contribution Analysis into a method of choice for detecting this type of causality.

In contrast to counterfactual causation, *generative causation* understands causality by means of *causal mechanisms* (Pawson, 2008; Pawson & Tilley, 1997; Stern et al., 2012). With respect to generative causality, causal mechanisms are the "choices and capacities which lead to regular patterns of social behavior" (Pawson & Tilley, 1997, p. 216). They are understood as part of the realist proposition that "causal outcomes follow from mechanisms acting in contexts" (Pawson & Tilley, 1997, p. 58). Beyond the realist tradition, causal mechanisms represent a frequently used but not uniformly defined concept (Astbury & Leeuw, 2010; Weller & Barnes, 2014) that is still being researched (Lemire et al., 2020; Schmitt, 2020). John himself described generative causation pragmatically as a "stepwise perspective" that saw "causality as a chain of cause-effect events," embodied by the Theories of Change used in Contribution Analysis (Mayne, 2019c, p. 174). In another article in this special issue, Leeuw (2023) offers a more detailed analysis of how mechanisms are understood and examined in Contribution Analysis compared to other approaches.

Another account—*INUS causality*—was introduced by John Mackie in 1965 as part of the broader regularity approach to causation (Mackie, 1965, 1980; Mumford & Anjum, 2014; Sandahl & Petersson, 2016). Mackie described interacting causes that, together rather than separately, produce an effect. To do this, he leaned on the terms "sufficiency" and "necessity" with which he described the INUS condition for cause and effect:

> In this case, then, the so-called cause is, and is known to be, an *insufficient* but *necessary* part of a condition which is itself *unnecessary* but *sufficient* for the result. . . . In view of the importance of conditions of this sort in our knowledge of and talk about causation, it will be convenient to have a short name for them: let us call such a condition (from the initial letters of the words italicized above), an inus condition.
>
> (Mackie, 1965, p. 245)

Finally, *probabilistic causality* moves away from determinism by framing causation in terms of probabilities. In this account, causes increase the probability of effects, rather than deterministically causing them (Hitchcock, 2022; Mumford & Anjum, 2014; Sandahl & Petersson, 2016).

In addition, many other accounts of causation have been developed. Together with the above-mentioned accounts they are described in textbooks and articles from the field of evaluation (e.g., Stern et al., 2012, including the Annex by Befani; Sandahl & Petersson, 2016) and from other disciplines (Causality, 2022; Gopnik & Schulz, 2007; Hart & Honoré, 2002; Illary & Russo, 2014; Kleinberg, 2013; Moore, 2010, part VI; Morgan, 2014; Mumford & Anjum, 2014; Paul & Hall, 2013; Pearl, 2009, including the Epilogue; Pearl, Glymour, & Jewell, 2016; Pearl & Mackenzie, 2018; Salmon, 1998; Waldmann, 2017).

When dealing with different accounts of causation, it is important to understand that different accounts explain the *nature*, *essence*, or *ontology* of causality in different ways. On this fundamental level, they *define* causality differently and offer different explanations of what causality *is*.

Among the many methods that can be used to infer causality, some are more suited than others depending on which type of causality is to be detected (Table 1). A simpler way to say this, which was often used by John, is that some methods are better suited to answer specific causal questions than others.

For example, in instances when it can be applied meaningfully, the *Randomized Controlled Trial* (*RCT*) is considered a suitable experimental method for inferring counterfactual causality. The method mimics the hypothetical world in which the intervention did not take place by means of a control group, and then compares it with the real world in which the intervention has taken place (the treatment group). As a result, RCTs can *attribute* results to an intervention (i.e., determine how much change is caused by the intervention).

In a similar vein, when it can be applied meaningfully, *Contribution Analysis* represents a suitable theory-based method for inferring generative causality, as explained in more detail in the next section. In its present form, its focus lies on determining whether—and to what degree—an intervention has *contributed* to an observed change.

This said, a method suitable for inferring one type of causality can also be useful for inferring another. This is because different causality accounts essentially aim at describing the same thing: what humans intuitively consider cause

**Table 1.** Types of causation

| Type of causality | "Preferred" method for inferring this type of causality | Examples for causal questions |
|---|---|---|
| Counterfactual causation | Experimental or quasi-experimental methods | How much change has been caused by the intervention? |
| Generative causation | Theory- or process-based (realist) approaches | How and why has the intervention contributed to change? |
| INUS causation | Configurational and case-based approaches | Was the intervention a necessary part of a sufficient causal package for the observed change? |
| Probabilistic causation | Statistical approaches | How much more likely is the change because of the intervention? |

*Note*. Adapted from Stern et al. (2012) and Mayne (2020).

and effect in their daily lives. As a consequence, different accounts of causation overlap in what they deem causal, and a method that is well suited for one account can also have some merit for inferring another type of causality. In addition, the similarities between different accounts also mean that methods suited for one type of causality can sometimes usefully "borrow" and integrate concepts from other causality accounts. This will become evident in the fourth and fifth sections. But first, the close linkages of Contribution Analysis to the generative account of causation are summarized.

## MAKING A DIFFERENCE—INFERRING GENERATIVE CAUSALITY WITH CONTRIBUTION ANALYSIS

In 2019, John described the key question Contribution Analysis set out to answer as follows:

> Did the intervention make a difference, i.e., play a positive causal role in bring [*sic*] about the observed results? In particular, how and why has the intervention made a contribution? What causal (support) factors are needed for the intervention to make a contribution?
>
> (Mayne, 2019b, p. 6)

Contribution Analysis then could provide an answer to this question by evidencing a *contribution claim* with the following syntax: "The intervention (or a component) contributed to an observed change—it played a positive role in bringing about change—and it did so in the following manner"

(Mayne, 2019b, p. 5). With this, John emphasized that evidence-based contribution claims must not only demonstrate *that* the intervention played a positive role in bringing about an outcome. They must also explain *how* and *why* this happened.

Towards this end, Contribution Analysis follows a seven-step process to establish that contribution claim (Exhibit 1). Reflective of how the approach is firmly rooted in generative causality, it employs Theories of Change to model causal pathways and assumptions, and to structure the analysis. In John's own words:

> The basis of the contribution claim is the empirical evidence confirming a solid ToC [Theory of Change] of an intervention, i.e., confirming the chain of results, the assumptions behind the causal links in the ToC and the related causal narratives explaining how causality is inferred. The ToC is the outline for the contribution story of the intervention.
>
> (Mayne 2019b, p. 2)

As described until now, the contribution claim essentially represents a yes/no type of answer to the question "did the intervention make a difference?" By working through the Contribution Analysis steps, one can gradually increase the level of confidence in the contribution claim: "From a state of not really

Step 1: Set out the specific cause-effect questions to be addressed

Step 2: Develop robust theories of change for the intervention and its pathways

Step 3: Gather the existing evidence on the components of the theory of change model of causality:

- The results achieved
- The causal link assumptions realized

Step 4: Assemble and assess the resulting contribution claim, and the challenges to it

Step 5: Seek out additional evidence to strengthen the contribution claim

Step 6: Revise and strengthen the contribution claim

Step 7: Return to Step 4 if necessary

**Exhibit 1.** Steps in Contribution Analysis

*Note.* Mayne (2019b).

knowing anything about how a program is influencing a desired outcome, we might conclude with reasonable confidence that the program is indeed having an attributable impact; that it is indeed making a difference" (Mayne, 1999, p. 5). In the early years of Contribution Analysis, John suggested to address this issue by requiring that the intervention had made a "significant"—in the sense of relative importance but without implying any statistical significance—contribution to intended outcomes, whereas external factors—other contributing causal factors unrelated to the intervention—had not (e.g., Mayne, 2019). If, instead, external factors played a significant role, they needed to be recognized in the contribution claim (e.g., Mayne, 2012a) or, if that was impossible, the contribution claim could not be proven.

Without further guidance, this leaves much room for interpretation about exactly when a demonstrated causal linkage between the intervention and its intended outcome is important enough for the intervention to qualify as having made a difference. In our discussions on the subject, John wondered if a more nuanced contribution claim might be possible; one that gave a sense of magnitude of how important the intervention was for the observed outcome.

In this context, John became interested in exploring ways to assess the relative importance of the intervention in relation to other, external factors in a more systematic way. In 2018 and 2019, John argued that the "relative importance" of causal factors could be interpreted in several meaningful, complementary ways, as follows (Mayne 2019a):

1. *Perceived influence* of the causal factor in bringing about a change. This could be operationalized by asking targeted stakeholders in interviews or a survey to rank the perceived influence different causal factors had had, for example on their changed behavior.

2. The *role played* by the causal factor in bringing about a change. For example, whether a causal factor had triggered, supported, facilitated, or accelerated change.
3. The *funds expended* by the causal factor. John considered this useful when funding scaled with different levels of activity but not for causal factors that represented conditions unrelated to funding.
4. The *difficulty of bringing about a causal factor*, reflecting the level of focus, energy, and effort required to generate the causal factor.

John suggested that comparing importance rankings across several or all of these notions of importance might be a good strategy for informing conclusions about relative importance.

In spite of these attempts to better handle questions of relative importance of the intervention at hand compared to that of other causal factors, John himself did not offer a more rigorous approach for establishing the *significance* of the intervention's contribution, or the degree to which it had *made a difference* (other authors, for example Lemire, Nielsen, Dybdal [2012], however explored this question further). Instead, John relied on the ability of evaluators—in view of the thorough understanding the approach offers regarding *how* the intervention and other factors had contributed to observed change—to pass a judgment on relative importance.

## METHODS INTEGRATION—ELEMENTS OF OTHER CAUSATION ACCOUNTS IN CONTRIBUTION ANALYSIS

John's practical and solutions-oriented approach to research and his ability to easily operationalize theory in practice is described by Nielsen, Lemire, and Montague (2023) in the opening article of this special issue. John therefore did not hesitate to make use of concepts from other causality accounts if they could be usefully integrated with the framework of Contribution Analysis. This was comparatively easy because the Contribution Analysis leaves considerable analytical freedom regarding the tools and methods used in addressing each of the seven Contribution Analysis steps (Exhibit 1).

John's participation in an influential study on designs and methods for impact evaluation (Stern et al., 2012) inspired him to borrow the concepts of *causal packages*, *causal necessity*, and *causal sufficiency* from Mackie's *INUS account of causation* (Mackie, 1965, 1980; Mumford & Anjum, 2014; Sandahl & Petersson, 2016). John used these concepts to further refine what *making a difference* meant. An intervention was *making a difference* if it was a *contributory cause* for an observed outcome. A contributory cause, in turn, was a causal factor that was—by itself—neither necessary nor sufficient for the outcome to be realized. In other words, this means that the outcome could also be produced by other causal factors, and that the presence of the factor, by itself, did not yet guarantee the outcome. At the same time, a causal factor that constituted a contributing cause was a necessary part of a causal package that—as a whole—was sufficient for the outcome to occur.

In other words, the group of factors to which the contributing cause belonged could not produce the outcome without it, and all factors of the group together guaranteed the outcome. Taken together, these criteria closely mirror Mackie's INUS condition.

In subsequent publications (Mayne, 2012b; Mayne & Stern, 2013), John equated that an intervention was *making a difference* with it being a contributory cause, and defined it as follows:

1. The intervention causal package was sufficient to produce the observed result.
2. The intervention was a necessary element of the causal package.

At the same time, John also borrowed from *probabilistic causality*. Using probabilistic language, John began referring to *likely necessary* and *likely sufficient* conditions in the context of Contribution Analysis. He considered them more realistic interpretations than their deterministic INUS peers:

> Following on from Mahoney [2008], in terms of the intervention causal package, I suggest the term likely necessary to describe the supporting factors that are usually, or almost always have to be, present for the outcome to occur. And I suggest likely sufficient to describe the sufficiency of the intervention causal package, meaning that, in this case, the causal package most likely produced the observed result. For an intervention being evaluated, these are more realistic interpretations of the necessary and sufficient conditions as discussed earlier.
>
> (Mayne, 2012b, p. 2)

In this way, John borrowed concepts from two other causality accounts and integrated them into the Contribution Analysis approach to further clarify and generalize the approach.

In contrast, John struggled with the relation another causality type—*counterfactual causation*—had with Contribution Analysis, particularly regarding the question of whether the approach could—and should—be used to also answer typical counterfactual causality questions.

## CAN—AND SHOULD—CONTRIBUTION ANALYSIS BE USED TO INFER COUNTERFACTUAL CAUSALITY?

In counterfactual causality, a key question of interest is how much of an observed outcome can be *attributed* to an intervention. Following counterfactual reasoning, this is understood as the difference between the observed outcomes in the real world in which the intervention took place and a hypothetical world where it didn't.

In our discussions, John called this the "how much" question. He felt that it represented somewhat of a paradox. On the one hand, he knew that Contribution Analysis was not the method of choice for addressing counterfactual causality

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questions. Over time, as explained in more detail below, John also grew increasingly weary of how meaningful such questions were for the complex programs he worked with.

On the other hand, John was aware of the strong demand for counterfactual information of the "how much" type. A recent publication coauthored by John summarized this paradox as follows:

> While contribution analysis provides a step-by-step approach to verify whether an intervention . . . is a contributory factor to development, most contribution analysis studies do not quantify the "share of contribution" that can be attributed to a support intervention. Generally, in most interventions, there are multiple actors involved in the process of change, and it seems unreasonable and inherently impossible to attribute these effects entirely to one actor. However, commissioners of evaluations often want to have an idea about the size or importance of a contribution of one of the actors (the one they fund), not least because they need this information at an aggregate level for accountability to parliament. This creates the paradox that commissioners of impact evaluations pose legitimate but unanswerable questions, and impact evaluations need a way to reconcile the impossible with the possible.
>
> (Ton et al., 2019)

Initially, however, John made frequent use of attribution language when describing his method. For example, his first two publications on the subject in 1999 and 2001 were titled "Addressing Attribution Through Contribution Analysis." At that time, John stressed the importance of acknowledging the "attribution problem" (Mayne, 2008) and wrote that Contribution Analysis should determine "How much of the success (or failure) [we can] attribute to the program?" and that "We might also be able to provide a reasonable estimate of the magnitude of the impact" (Mayne, 1999, pp. 3 and 5; 2001, pp. 3 and 6).

Then and later, John was adamant about the fact that the intervention represented only one causal factor among many. But in the first decade after he first published about Contribution Analysis, he did not exclude determining the relative importance of these causal factors by understanding what portion of outcomes could be attributed to the intervention.

This changed from about 2012, coinciding with the period when John integrated concepts from INUS and probabilistic causality into Contribution Analysis, and when the journal *Evaluation* dedicated a special issue to the approach (Mayne 2012a and other articles in that issue). Since then, John more clearly demarcated Contribution Analysis from the "how much" question—and generally from counterfactual causality. He positioned it firmly as a method for assessing generative causality. Rather than attempting to attribute outcomes to the intervention, Contribution Analysis was about demonstrating that the intervention was a "contributory cause" which had played a positive "causal role" in bringing about change (Mayne 2019c).

Starting from some years before that, John largely stopped using attribution language (Figure 1). In later years, he also objected to the overall usefulness of the counterfactual perspective: "In many situations a counterfactual perspective on

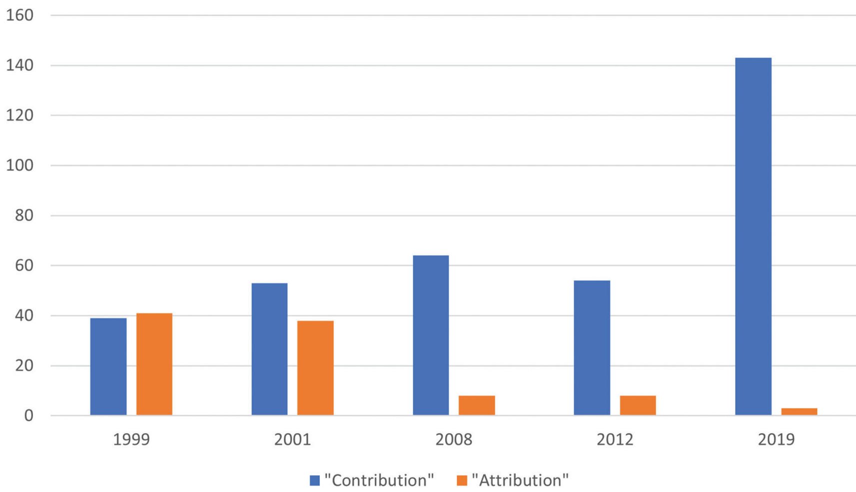


**Figure 1**. Number of times the terms "contribution" and "attribution" are mentioned in selected publications on Contribution Analysis

*Note*. Mayne (1999, 2001, 2008, 2012a, 2019c).

causality—which is the traditional evaluation perspective—is unlikely to be useful; experimental designs are often neither feasible nor practical" (Mayne 2019c, p. 174). John argued that counterfactual evaluation questions were "probably less than useful" in many instances and often represented "indeed questions that likely cannot be credibly answered as posed" (Mayne, 2021b, p. 160). To serve accountability, more meaningful questions should be asked, reflecting a broadened and more meaningful understanding of accountability which would include, for example, also accountability for learning.

Nevertheless, while increasingly positioning Contribution Analysis as a generative alternative to counterfactual methods, the "how much" question remained on John's mind. He felt that in order to represent a viable alternative, Contribution Analysis should offer more than only answering a yes/no type of question about whether an intervention had played a causal role for an observed outcome or not. This may have motivated the development of additional ideas and guidance on how to assess and rank the relative importance of causal factors, as outlined earlier. Moreover, John participated in research on how to make use of rankings and quantitative estimates of effect sizes for verifying Theories of Change and the resulting contribution stories in the context of Contribution Analysis (Ton et al., 2019).

## CONCLUSION

With Contribution Analysis, John established an important approach for systematically analyzing what causal role an intervention had played in bringing about change. John developed the approach to also address the more difficult question of how important that role had been compared to other causal factors at play. Over time, Contribution Analysis established itself as one of the approaches of choice for evaluating generative causality, building on the concept of causal mechanisms and on causal explanation.

At the same time, the Contribution Analysis protocol allows considerable methodological freedom, rendering the approach flexible towards how its analytical steps were applied in practice. In the words of one contributor to a special issue on Contribution Analysis, "Rigorous thinking supersedes rigorous methods" within this approach (Patton, 2012).

John was convinced that understanding and analyzing generative causality as a chain of cause-and-effect events was more useful and realistic than focusing on counterfactual causality, for the oftentimes complex public policy and development cooperation interventions he dealt with. In these instances, he knew that attributing observed outcomes to an intervention was, oftentimes, simply not possible. Moreover, he believed that even asking the counterfactual question of "how much" of those outcomes could be attributed to the intervention was usually not meaningful, at least not for the types of programs and interventions he was concerned with.

John described the central causal claim to be analyzed by Contribution Analysis by whether the intervention was "making a difference." This idiom could of course easily be misunderstood as a counterfactual statement—as referring to the difference between the world with the intervention and the hypothetical world without—and was a wonderful way to tease him in our discussions.

In contrast, for John, "making a difference" meant that intervention had been important relative to other causal factors, a causal claim firmly embedded into generative causality. This nuance represents one theoretical reason why Contribution Analysis can be applied where counterfactual methods cannot. Counterfactual methods require attribution of outcomes to the intervention. If that can be analyzed, it usually also means that the intervention has also been an important generative cause. However, beyond being able to incorporate such counterfactual findings, Contribution Analysis is open to also use other ways to demonstrate relative causal importance that are not part of counterfactual methodology. For example, John suggested that the stakeholder perceptions on causal influence, the causal role played by the intervention, the funds expended, or the difficulty to bring about a causal factor represented additional ways to establish whether the intervention had made a difference.

Reflecting his pronounced methodological pragmatism and his outstanding ability to bridge theory and practice described by Nielsen, Lemire, and Montague (2023) in the opening article of this special issue, John freely borrowed concepts from other accounts of causation and integrated them into the Contribution Analysis protocol. He used the concepts of sufficiency and necessity, and what John referred to as causal packages ("condition" in the original) from Mackie's INUS account of causation to better define the relative importance of the intervention at hand, vis-à-vis other causal factors. John used probabilistic language to render those definitions less deterministic and—in his view—more realistic.

Going forward, it is my hope that this methodological pragmatism prevails when further researching and developing John's Contribution Analysis.

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