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Strange Bedfellows: Exploring Methodological Intersections Between Realist Inquiry and Structural Equation Modeling

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Abstract

Realist inquiry, based on the philosophy of critical realism, focuses on exploring the underlying mechanisms that drive social phenomena. Structural equation modeling is a collection of quantitative analytical methods that take a theory-based, confirmatory approach to examining statistical relationships between measured (observable) and underlying (latent) variables. Despite originating from different scientific traditions, the apparent similarities between these two approaches hold promise for their combination in mixed methods research. This article contributes to the field of mixed methods research by exploring their potential synergies, how each approach could contribute to the other, and proposing a framework for their combinations in mixed methods research, which has implications in terms of the implied and explicit ontological and epistemological positionings of these two approaches.

Keywords

context, realist inquiry, structural equation modeling, mixed methods research, medical education

A key difference between research paradigms is how they deal with context. For some, context is the coincidental and arbitrary location of the things they are interested in, for others, context is a relationship (expressed in many different ways) within which things of interest are bound and shaped. Indeed, context is a major focus of inquiry in the social sciences (Cole, 1996; Flyvbjerg, 2001; Maxwell, 2012; Williams, 2003). Context can also serve as an intervention or mechanism. For instance, in the applied field of health professions education, learners are often placed in different contexts (e.g., hospital-based rotations, primary care clinics) as a way of catalyzing learning outcomes (Ellaway et al., 2016; Tesson et al., 2005; Walters et al., 2012). To that end, what configurations of contextualized learner experiences do (and do not) lead to what outcomes is a key concern of researchers in our field (Bates & Ellaway 2016; Norman, 2014;

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Regehr, 2006). Because of this, our research team has a particular interest in methods and methodologies that consider context in meaningful and constructive ways.

Combining context-sensitive techniques of inquiry would seem to afford benefits based on the different ways they model context and contextual dependencies. This article considers the mixing of two approaches to inquiry that deal with context directly: one a conceptual approach to inquiry that is often, but not exclusively, qualitative; the other a set of quantitative methods grouped under the umbrella concept of ''structural equation modeling'' (SEM). Our interest in these two approaches arose from an extended conversation around how we examine context in health professional education. KGH had experience using SEM methods (Hecker & Violato, 2009; Norris et al., 2017; Oliver et al., 2014; Violato & Hecker, 2007) and RHE had experience of realist methods (Ellaway et al., 2016; Ellaway et al., 2018). The methodological aims of this article are to explore the similarities, differences, and intersections of realist inquiry and SEM, as well as the practical and theoretical implications of combining these two approaches to inquiry.

Strange Bedfellows

Realist inquiry and SEM are, at first glance, strange bedfellows since they come from very different scientific traditions and are epistemologically heterogeneous. Moreover, they map to different stages in the arc of scientific inquiry: realist inquiry is about identifying causal relationships between entities within a system in order to explain the relationships between contexts, mechanisms, and outcomes; SEM is about statistically measuring the strength of relationships between latent and observed variables (which may or may not reflect constructs related to contexts, mechanisms, and outcomes) and developing quantitative models of those relationships.

Analyzing Mixed Methods

An important aspect of mixed methods research lies in exploring the implications of different combinations of methods. There have been various frameworks proposed for doing this, including sequencing models (Creswell et al., 2003) and affordance models (Greene et al., 1989). Nastasi et al. (2010) set out a descriptive framework for reporting mixed methods research at both the procedural and overall design levels (Nastasi et al., 2010). Underlying these models and the concerns they are intended to address are issues of shared and divergent methodological ontologies and epistemologies (Ghiara, 2020; Sandelowski et al., 2012). For instance, in comparing critical realist and constructivist epistemologies, Sommer Harrits (2011) called for clarification of the epistemological and ontological bases for combining methods in mixed methods research as well as the ontological basis and epistemological assumptions associated with each component method or methodology (Sommer Harrits, 2011). Sandelowski et al. (2012) instead focused on the internal logic of the component methods and the integrative logic of putting various methods together (Sandelowski et al., 2012).

Methodological Compatibility in Mixed Methods Research

Mixed methods researchers have long been concerned with the compatibility of different combinations of methods (Creswell, 2011; Creswell & Plano Clark, 2010; Maxwell, 2012; Tashakkori & Teddlie, 2003). For example, Ghiara (2020) considered the problem of incommensurability, the argument that if different methods share no common measures or philosophical assumptions they cannot be meaningfully combined (Ghiara, 2020). She rejected this thesis, noting instead that mixed methods research can benefit from the tensions and differences between methods as well as from their synergies and similarities. Howe (1988) echoed this in arguing for ''methodological eclecticism''—the idea that methods should not be intrinsically tied to a single paradigm (Howe, 1988).

In exploring the similarities, differences, and approaches and arguments for combining realist inquiry and SEM, we considered the internal ontological, epistemological, and logical bases of each approach, as well as the integrative ontological, epistemological bases of combining them. This article considers each in turn before going on to consider some of the practical issues that follow from combining these two approaches.

Realist Inquiry

Philosophical Underpinnings of Realist Inquiry

Realism, a position that the universe exists independent of our perceptions or conceptions of it, is a broad philosophical concept that has been applied in many branches of science. In the context of this article, our focus will be on the philosophy of critical realism as defined by Bhaskar (1975, 1989) and the methods associated with realist inquiry as developed by Pawson and his associates from critical realism (Pawson, 2006; Pawson & Tilley, 1997). Bhaskar's conception of realism was based on ''a three-layered ontological model including the empirical domain, consisting of experiences; the actual domain, consisting of events; and the real domain, consisting of causal mechanisms'' (Sommer Harrits, 2011). Critical realists work on the assumption that the social world is driven by causal mechanisms that exist even though these mechanisms may be inactive, not directly observable, or obscured or inhibited (Bhaskar, 1979). Given the complex and voluntarist nature of social phenomena, critical realism in the social sciences combines a realist ontology with a constructivist epistemology and primarily focuses on explaining how phenomena ''work'' and, from that, how they might be manipulated (Ellaway et al., 2020; Wong et al., 2012).

Associated Methods of Realist Inquiry

It is important to note that critical realism is not a methodology or even a method, it is a philosophical perspective from which methodologies and methods can be developed (Archer, 1995; Pawson, 2006) and with which they can be aligned. While the principles of critical realism have been translated to methodologies in different ways, the work of Pawson et al. (Emmel et al., 2018; Pawson, 2006; Pawson & Tilley, 1997) has received particular interest and uptake in the applied social sciences. Pawsonist realist inquiry focuses on programs and policies, social interventions that are applied across multiple contexts and that are expected to work more or less effectively, to be adapted in different ways, and to have varying outcomes according to context (Pawson, 2013; Pawson & Tilley, 1997). This approach was developed in part as a response to the limitation of objectives-oriented and reductionist approaches to researching and evaluating programs that focused on their a priori objectives, while disregarding variations in program functions and outcomes (Tyler, 1983). Rather than eliminating contextual effects and confounding variables, realist approaches acknowledge that programs are embedded in complex social systems, and that they are likely to work differently in different contexts and with different individuals. The essence of this approach was captured in the aphorism ''What works? For whom? In what circumstances? In what respects? and How?'' (Pawson & Tilley, 1997).

A program-focused approach to realist inquiry starts by outlining a provisional program theory as ''a plausible and sensible model of how a program is supposed to work'' (Bickman, 1987, p. 5). To that end, a program theory (originally developed in the context of program evaluation and social systems research (Wholey, 1987) is specific to the program under consideration and draws on evidence, observations, and expectations to establish a provisional framework to guide inquiry. A provisional program theory is used to generate realist research questions which can then be explored empirically.

Ontological Assumptions of Realist Inquiry

Ontologically, realist inquiry focuses on the interplay of contexts, causal mechanisms, and their outcomes, reflecting its postpositivist roots in critical realism. Realist inquiry is predicated on there being mechanisms that drive reality, even though these mechanisms may not be activated or directly observable for instance when ''they operate at different levels of the system than the outcome under investigation, they operate over different timescales, and they necessarily involve interactions that might not be observable'' (Westhorp, 2018, p. 56). Inferring mechanisms that may not directly observable is a key ontological stance of realist inquiry.

Epistemological Assumptions of Realist Inquiry

Epistemologically, realist inquiry's focus on mechanisms is essentially explanatory, seeking to understand why things are the way they are and how they might be changed. Despite its postpositivistic roots, realist inquiry typically employs social science methods as the only way to explore voluntarist and socially constructed phenomena, an approach Bhaskar called ''critical naturalism'' (Bhaskar, 1989). Methodologically realist inquiry is both eclectic and pragmatic in that it can employ many different kinds of methods and data as long as they reflect the contexts, mechanisms, and outcomes of the phenomenon under consideration. From a realist perspective, qualitative data can be analyzed using qualitative techniques, quantitative data using quantitative techniques, any and all of which should focus on answering ''what works, for whom, in what context?''

Contexts, Mechanisms, and Outcomes

Central to realist inquiry is the concept of a Context-Mechanism-Outcome configuration (often shortened to ''CMOc''; Pawson & Tilley, 1997), a triadic association that ''in this context, this mechanism led to or contributed to this outcome.'' A program may function across many contexts, have many mechanisms, and have many outcomes, all of which may be causally connected in many different ways. Contextual factors are those that influence the implementation of a program, including macro-level factors (i.e., organizational culture, politics, and economics) and micro-level factors (i.e., participant characteristics, relationships between participants, and specific activities). Mechanisms are the underlying processes that influence the behaviors of program participants (Astbury & Leeuw, 2010); they shape the ability and willingness of individuals to act or not act, or to act in certain ways (Lacouture et al., 2015). For instance, a mechanism may create opportunities for action (e.g., funding allowing for additional workers or equipment), it may inhibit them (e.g., a restrictive policy or social more), or it may direct toward certain kinds of action over others (e.g., pushing toward competitive rather than collaborative social relations). Finally, outcomes are the results and impacts of a mechanism acting within a particular context, both expected and unexpected.

It is important to note that what counts as a context, mechanism, or outcome is defined within the relationship between entities in a Context-Mechanism-Outcome configuration rather than as an intrinsic property of the entities: one configuration may create the context for another or be nested within another configuration, and so on. A system involving multiple actors and activities may be explained in terms of chains and networks of Context-Mechanism-Outcome configurations related to the behaviors of different actors rather than single independent mechanisms working toward single independent outcomes. Moreover, the distinction between context (a background influence) and mechanism (a foreground influence) is not often distinct (Lacouture et al., 2015). Resolving these issues is an abductive process (Douven, 2017) that may employ retroduction (reasoning from contexts and outcomes to mechanisms, essentially asking ''what is making this outcome happen?'') or retrodiction (reasoning from mechanisms and contexts to outcomes, essentially asking ''what outcomes is this mechanism likely to produce?'')—or a combination of both (Elger, 2012).

Although analyzing the relationships between contexts, mechanisms, and outcomes predates their reification in a formal method (Pawson, 1989), it was Pawson (2006) who proposed a structured approach of identifying, recording, and analyzing Context-Mechanism-Outcome configurations from the available data (Pawson, 2006). This approach is based on analyzing these configurations in aggregate for recurring elements or ''demi-regularities''—explanations about how and why certain kinds of mechanisms may generate certain kinds of outcomes when triggered in certain kinds of contexts (Lawson, 1994; Pawson, 2006). Demi-regularities can be further consolidated to establish ''middle-range theories,'' explanatory statements about the general functions of the program (and by implication of similar programs in similar circumstances; Merton, 1949). In this way, Pawsonist realist inquiry does not seek to generate general theories applicable to all systems or all contexts. Closing the loop in program-focused approach to realist inquiry involves revising the initial program theory to reflect the findings from the empirical stages of the study, refining the explanations of how a program ''works.'' The findings may then be used to guide changes to the program (usually by manipulating the mechanisms that drive certain outcomes) or inform further cycles of inquiry (Wong et al., 2012). This arc of inquiry, from program theory to empiricism and back to program theory, may happen once or many times. The principles of realist inquiry can also be used as a conceptual framework for secondary knowledge syntheses (i.e., realist synthesis) and program evaluations (i.e., realist evaluations), and as a guiding philosophy for qualitative research (Greenhalgh et al., 2011; Maxwell, 2012).

Additional Methods and Perspectives Associated With Realist Inquiry

Although the Pawson model of realist inquiry is a dominant one, there have been other approaches to translating critical realism into a methodological stance. For instance, Fletcher's analyses stay closer to Bhaskar's concepts of critical realism in that they can be both abductive (where ''empirical data are redescribed using theoretical concepts'') and retroductive (drawing out causal mechanisms and the necessary conditions for those mechanisms to work; Fletcher, 2017). Another example is Archer's (1995) three-stage ''morphogenetic cycle'' that involves identifying the agents in a system, identifying the social changes arising from interactions between these agents, and then analyzing how the resources available to these agents afford or inhibit action.

In summary, realist inquiry is a pragmatic (adaptive) and abductive (explanatory) methodological frame of inquiry that has particular utility in exploring how complex systems and programs work and from that how they can then be manipulated to achieve different outcomes (Pawson, 2013). Realist inquiry does not require a single method or approach. Rather, realist scientists utilize the most appropriate methods to explain how different phenomena work, a principle that has also been argued for in mixed methods research (Howe, 1988). Although realist inquiry is not intrinsically mixed methods, realist studies often employ mixed methods as a response to the complexity of the systems they are trying to explain. The limits of realist inquiry include its procedural breadth, its intrinsically idiographic (context-bound) frame of inquiry, the challenges of exploring mechanisms that are inactivated or obscured, and the necessary parsimony required in exploring complex social systems.

Structural Equation Modeling

The Historical Development of Structural Equation Modeling

While realist inquiry has explicit roots in the philosophical concepts of critical realism, the discourses of SEM have mostly focused on its technical development and on its internal logic and processes rather than on its conceptual or philosophical roots (Bollen, 1989; Kline, 2016). Nevertheless, Tarka (2018) noted that while SEM has its philosophical roots in measurement theory, it was developed across multiple fields including psychology (Spearman, 1904), genetics (Wright, 1934), mathematical modeling (Thurstone, 1931), and econometrics and sociology (Blalock, 1963). The common factor in all of these developments is a focus on seeking out and testing causally dependent relationships between variables using quantitative data. Given that there has been little written about the ontology and epistemology of SEM, we provide our own analysis of its conceptual bases rather than drawing on others' assertions and interpretations.

SEM emerged in the 1970s as a way of integrating factor analytic methods, path analysis, model estimation, and ''goodness of fit'' techniques (Bollen, 1989; Hauser & Goldberger, 1971; Jöreskog, 1970). Path analysis was first defined in 1921 by Wright, where relationships (''paths'') are first articulated between both independent and dependent measured variables and the interrelationships are then estimated to determine the strength and significance of each relationship (Li, 1975; Wright, 1934). Factor analysis was first described by Spearman in 1904, who attempted to assess how measurable characteristics relate to latent constructs that are not directly observed but are hypothesized to exist, such as intelligence (Spearman, 1904). This work provided the foundation for exploratory and confirmatory factor analysis (EFA and CFA, respectively). CFA became a core constituent of SEM. SEM developed as a way of modeling hypothesized relationships between manifest (i.e., directly observable) or latent (i.e., unobservable) variables in order to develop and refine theories.

Ontological Assumptions of Structural Equation Modeling

Ontologically, SEM can also be considered postpositivist in that it is based on a fundamental assumption that things exist in the world independent of our knowledge of them but our means to explore this reality are imperfect. Central to this is the differentiation between the measurable and observable variables in a system and its underlying (latent) variables. Although latent variables are assumed to exist (and are often the primary focus of SEM analyses) it is also understood that they cannot be directly observed or measured. More recently, Hathcoat and Meixner (2017) described the associations between EFA with principles of realism, but did not extend this argument to SEM (Hathcoat & Meixner, 2017).

Epistemological Assumptions of Structural Equation Modeling

Epistemologically, SEM focuses on building and testing models of hypothesized (theoretical) relationships between measured variables and latent constructs, thereby generating multivariate evidence of causal mechanisms. Latent constructs (such as professionalism, aptitude, or empathy) cannot be directly observed or measured. In SEM, constructs can be modeled using observed variables as a series of proxy measures for the construct of interest (e.g., ratings of performance or numbers of errors). SEM attempts to identify shared variance on the measures of interest based on the assumption that the variance is the true signal, rather than as noise or error. More important, SEM allows for hypothesized relationships between latent constructs (structural equations) to be explored. SEM is typically confirmatory (rather than exploratory), seeking to fit data to proposed models and more importantly, based on the covariance matrix of all data provided, indicating where variables, directly or indirectly affect the construct(s) of interest.

Methods of Structural Equation Modeling

A full SEM, referred to as a ''latent variable path analysis'' has two components. The first involves creating one or more measurement models that are built from CFAs to represent how latent variables are measured by indicator (behavioral) variables. The second involves creating one or more structural models that depict relationships between latent variables. The foundation of these models is path analysis, which allows researchers to hypothesize relationships between variables, including causal relationships based on the strength and the direction of the correlations.

SEM requires large numerical data sets in order to test these hypothetical relationships. Indeed, the quantity and quality of the data used in SEM directly shape the quality of the findings and the strength of the inferences that SEM can generate. Reliability and validity evidence (i.e., numerical estimates regarding the psychometric properties of the data, such as reliability and correlation coefficients, etc.) are needed to ensure that the data can be used to generate inferences and later integrated into a structural model. Essentially, underlying constructs (i.e., intelligence) are represented through observed variables.

Typically building and testing a SEM involves: (a) articulating a research question and specifying the model (defining the relationship between the structural and measurement models) based on theoretical knowledge and/or empirical findings, (b) determining whether or not a model's parameters (which indicate associations or relationships between variables) can be tested using SEM techniques, (c) establishing how well the model fits the observed data, (d) generating numeric estimates of the ''goodness of fit'' of the observed data to the model, and (e) examining fit indices. This cycle iterates, developing and testing structural models until the data sufficiently fits the model (Bollen & Long, 1993; Kline 2016; Violato & Hecker, 2007 for more procedural information).

Strengths and Limitations of Structural Equation Modeling

SEM has several strengths. First, it can be used to test theories by quantifying hypothesized relationships between observed measures and underlying latent constructs (Kline, 2016). Second, and perhaps more importantly, SEM can be used to further explore and test direct and indirect relationships between latent constructs in both linear and nonlinear models through the use of multivariate analyses (Kline, 2016). Finally, SEM allows contextual variables to be integrated within a model to determine whether they have mediating and moderating effects. Mediator variables are understood as causing indirect effects on other variables through a causal pathway, whereas moderator variables cause ''conditional effects'' between variables.

Limits to SEM include its need for inputs that may not always be readily available to researchers, such as a well-developed theory, large sample sizes, and the use of instruments that produce ''reliable'' scores (Violato & Hecker, 2007). SEM requires large sample sizes—even for the simplest of models. A recommended sample size-to-parameter ratio is 20:1, thus, more estimates are required for more complex models, ultimately requiring a larger sample size (Jackson, 2003). There are also epistemological issues regarding the ability of SEM to create

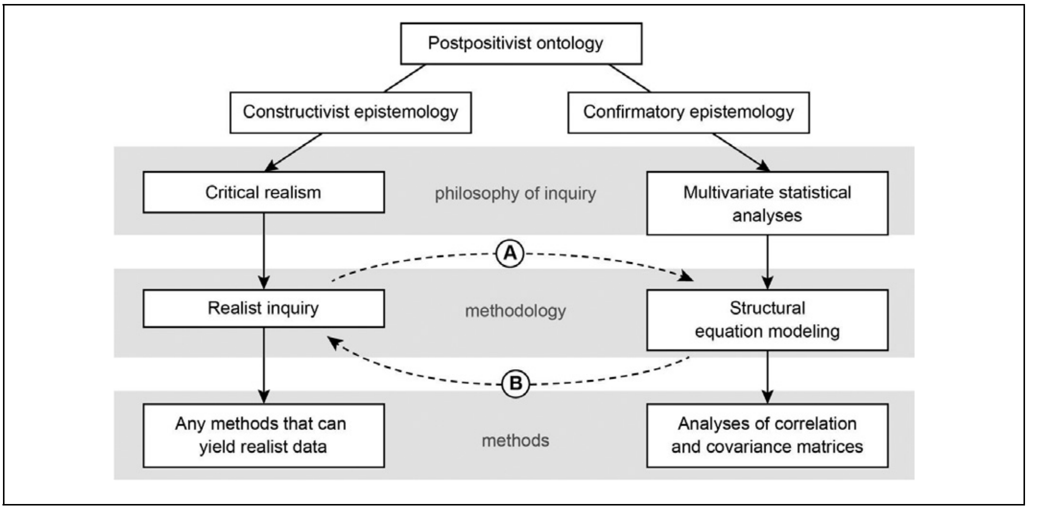

Figure 1. Different levels of inquiry comparing realist inquiry and SEM and their overarching philosophical connections. In this article, our research team's focus is on how realist inquiry might support SEM (A) and how SEM might support realist inquiry (B).
Note. SEM = structural equation modeling.

mathematical models of complex social systems, given that SEMs are by necessity a simplification of regularities within a complex reality (Cartwright, 1999, 2000; Rogosa, 1987, 1988). Finally, the use of data in SEM that have poor reliability or validity evidence is also likely to result in error and fail to generate inferences that are trustworthy. For models that are using data where reliability of scores may be low, even larger samples are needed to offset potential measurement error.

In summary, SEM is a confirmatory, theory-based methodology that can be used to build and test theoretical models using empirical observations, and provide quantitative estimates of the strengths of relationships between variables within the models it generates by combining both measurement and structural models.

Comparing and Contrasting Realist Inquiry and Structural Equation Modeling

We first consider whether researchers can meaningfully compare and contrast realist inquiry and SEM at all. Ontologically, realist inquiry and SEM are both based on assumptions about the causal nature of reality. However, although ontologically similar (postpositivist, focus on multiple interacting factors, etc.), realist inquiry and SEM differ epistemologically: realist inquiry has a strong conceptual and philosophical basis but a relatively open procedural approach, whereas SEM consists of a procedural set of techniques that are firmly situated within a measurement paradigm. Realist inquiry and SEM can be compared at these different levels—see Figure 1. Based on this, one might expect some level of commensurability between the two approaches while also noting their differences.

We built on this by comparing and contrasting different aspects of realist and SEM methods. Ontologically, critical realists work on the assumption that there is a real world around us that is driven by underlying mechanisms that may or may not be directly observable. Similarly, structural equation modelers assume that latent constructs exist but cannot be directly measured. The distinction between observed and latent variables in SEM is not directly mirrored in realist inquiry but it does reflect the realist concept of ''transcendental realism'' in that mechanisms exist whether they can be directly observed.

Shared Characteristics

Realist inquiry and SEM both employ methods that are theory-driven and explanatory, and both can be used to explore how different components of a system contribute to its function and outcomes. In SEM, a graphical model specification based on theory and evidence is developed to articulate proposed relationships between measured and latent variables before hypothetical models are tested for fit to data. Similarly, a program-focused approach to realist inquiry explores and explains the likely functions of a program in terms of intersecting elements in the form of a program theory (often articulated in the form of a logic model; Wong et al., 2013). SEM models and logic models (as part of realist inquiry) share a graphical analytical starting point.

Realist inquiry and SEM both focus on exploring and explaining causality through the examination of underlying mechanisms (realist inquiry) or mediators or moderators (SEM). In doing so, both methodologies embrace complexity, interdependency, and nonlinearity. Procedurally, they involve iterative testing and refinement of either a program theory (realist inquiry) or latent variable path analysis (SEM). Both approaches specify provisional theories or hypotheses about phenomena and then test them using empirical findings. If the data does not support their initial theories, then researchers in both realist inquiry and SEM rework their models or program theories to better fit their findings. Thus, both approaches are open for further testing and refinement against and with empirical data. To that end, although their terminology differs, SEM and realist inquiry are both hypothesis-generating and hypothesis-testing.

Key Differences

As much as realist inquiry and SEM share a number of characteristics, there are also key differences between them:

1. Despite both being predicated on the expectation that there are multiple coincident and/or dependent mechanisms at play within a system, realist inquiry methods are used to identify and describe these mechanisms, while SEM is used to quantify and validate the articulated relationships between them. This means that only quantitative data can be used in SEM, whereas realist inquiry can include data in many forms, and from many sources. Moreover, SEM requires large samples of high-quality quantitative data, that is, data that is supported with reliability and validity evidence (Brennan, 2006; Crocker & Algina, 1986; Nunnally & Bernstein, 1994), whereas realist approaches take a more pragmatic and inclusive approach to the data they might use. This has implications for how each methodology articulates concepts of reliability and validity.
2. The two approaches differ in their understanding of causality. SEM takes a successionist approach to causality (causal relationships are modeled in terms of interconnected variables and the relative strength of their connections and associations), while realist inquiry takes a generative approach to causality (explaining how and why different mechanisms in different contexts produce different outcomes; Pawson, 2008).
3. Realist inquiry focuses on context as a modifier/mediator of mechanisms and their outcomes. SEM on the other hand considers contextual factors in terms of multiple coincident factors that shape the behavior of a system, a departure from other quantitative approaches that typically seek to isolate and control variables. Analytical methods are used in SEM to establish the extent to which the model fits the data (i.e., goodness-of-fit indices), and whether models should be

redesigned in order to better explain the data. However, there is no equivalent quantitative indicator of the accuracy of a program theory in realist inquiry, or the strengths of relationships within and between Context-Mechanism-Outcome configurations.

4. The end result of realist inquiry is an explanatory model for how a system works in terms of its Context-Mechanism-Outcome configurations, demi-regularities, and middle range theories. Analysis in SEM provides quantitative account of the strength of relationships between all variables in the model in the form of standardized and/or unstandardized estimates (e.g., regression coefficients correlation coefficients) while embracing factors such as measurement error. Both talk to the multifactorial nature of the phenomenon under consideration, but in very different ways.
5. The paradigmatic differences between realist inquiry and SEM are also reflected in the concepts, symbols, and syntax each methodology uses. For instance, realist inquiry employs the concept of ''program theory,'' which in SEM would be considered a ''latent variable path program model.'' Realist inquiry can both test and generate middle-range (context-specific) theories, while SEM focuses on a more global concept of theory bound by the concept of ''goodness of fit.'' There are also differences in the visual syntax used for diagrams and models in each approach. There are no particular rules structuring how program theory diagrams should be expressed in realist inquiry, whereas SEM has a formal visual syntax for expressing its path models. Bhaskar's concept of ''transcendental realism'' included the idea that a posited mechanism way be real even if it cannot be directly observed (as it may not be activated, it may be obscured by other ''louder'' mechanisms, or it may be blocked or diverted by other mechanisms; Bhaskar, 1975). This is ontologically similar to the concept of the ''latent variable'' in SEM (a variable that cannot be directly observed but can be inferred from the behaviors of those variables that can be observed). Clearly, combining realist inquiry and SEM in mixed methods research designs would require a careful mapping between these constructs; we revisit this point later in the article.

In summary, although they have very different origins and there are key differences between them, there are many similarities between realist inquiry and SEM (Table 1). Our next step was to explore ways in which these approaches might be used together.

Combining Realist Inquiry and Structural Equation Modeling

The appraisal of mixed methods research designs can take many forms, including considering: the logical flow of mixing methods, including what is passed between methods and what is not; the theoretical, conceptual, and philosophical consequences of different mixed methods research combinations; and the strengths, weaknesses, advantages, and limitations of different combinations (Creswell, 2011; Creswell & Plano Clark, 2010; Tashakkori & Teddlie, 2003). We started by considering the logical flow of combining realist inquiry and SEM methods. In doing so, our research team drew on Creswell's (2011) typology of different kinds of mixed methods research, based on the logical sequencing of different methods—see Figure 2.

- *Explanatory Sequential Design*: SEM followed by realist inquiry: An initial SEM phase could be used to establish a latent variable path model which could then be elaborated in a subsequent realist inquiry phase. For instance, an SEM model could be used to inform the initial program theory for the realist inquiry phase of a study.
- *Exploratory Sequential Design*: Realist inquiry followed by SEM: Since one of the three inputs for SEM are causal assumptions (Pearl, 2012), the initial assumptions incorporated into an SEM model could be informed by a preceding realist inquiry phase. For instance, realist inquiry could be used to identify mechanisms that drive outcomes within a particular program or context, which could then be used to map out a provisional latent variable path model for testing and development in an SEM phase.

Table 1. An Overview of the Differences Between Realist Inquiry and Structural Equation Modeling.

	Realist inquiry	Structural equation modeling
What it is	• Philosophy of inquiry	• A collection of methods
Philosophical underpinnings	• Critical realism, post-positivism	• Positivism, postpositivism
Associated methods	• Identifying Context-Mechanisms-Outcome Configurations and the relationships between them, abduction, retroduction, retrodiction	• Identifying relationships between observed and latent variables using, but not limited to, factor analysis, path analyses, measurement
Data	• Open to any kind of data that can meaningfully answer a realist research question	• Large samples of quantitative data that have met the psychometric assumption of reliability and validity
Focus of inquiry	• Works in socially situated systems, such as programs and other multicontextual, multifactorial interventions	• Quantifying the relationships between plausible models of social and biological systems
End result	• Explanatory model articulating relationships between Context-Mechanism-Outcome configurations; middle range theories, demi-regularities	• A statistical model that is meant to describe causal relationships between latent and observed variables

- *Convergent Design*: Realist inquiry and SEM in parallel then results combined: An SEM component might be used to test a model or models against gathered data while a parallel realist inquiry component might be used to identify Context-Mechanism-Outcome configurations and demi-regularities in the function of the same program. The two sets of results could then be compared for similarities and differences, and the results synthesized to generate a more comprehensive model of the program than either method could provide on its own. SEM findings may quantify relationships between contexts, mechanisms, and outcomes identified from realist inquiry.
- *Multiphase Design*: Alternating use of SEM and realist inquiry over a period of time, for instance, a realist phase, followed by SEM, followed by another realist phase. Realist inquiry could be used to develop an initial program theory that could be subsequently tested using SEM (similar to the exploratory sequential design), but then uses realist methods to interpret and further refine program theories.

The Potential Advantages of Combining Realist Inquiry and SEM Methods

Combining realist inquiry and SEM could be iterative or cyclical, each building theory and models and testing them against the data. Explicit combinations of these techniques could be used to advance understanding of which theoretical model (or combination of models) fits the data best, and the nature of the relationships between variables within different models. This can be expanded on by considering the strengths and weaknesses of different approaches using the framework developed by Greene et al. (1989). The logical and procedural strengths of each combination are set out in Table 2.

We would stress that there is no apparent superordinate model of combining the two methodologies or any one approach that we see as intrinsically superior or of greater value than any other. Rather, different combinations of the two methodologies have the potential to be used to achieve different ends. The opportunities that different combinations of realist inquiry and SEM

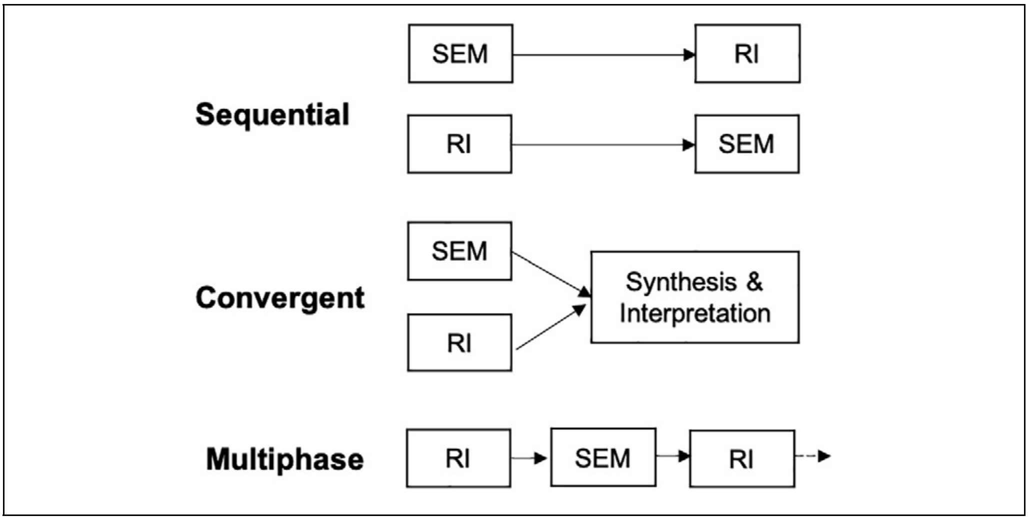

Figure 2. Mixed methods designs combining RI and SEM (based on Creswell, 2011).
Note. RI = realist inquiry; SEM = structural equation modeling.

Table 2. Matrix of Different Structural Equation Modeling–Realist Inquiry (SEM-RI) Mixed Methods Research Typologies (After Creswell, 2011) to Different Purposes (After Greene et al., 1989).

	Triangulation (convergence, corroboration, correspondence)	Complementarity (elaboration, enhancement, illustration, clarification)	Development (results from one method are used to develop or inform the next)	Initiation (contradictions, changing perspectives, and interpretations)	Expansion (each method expands the breadth of inquiry)
Explanatory sequential design—SEM followed by RI		•	•	•	•
Exploratory sequential design—RI followed by SEM		•	•	•	•
Convergent design—RI and SEM in parallel	•	•		•	
Multiphase design	•	•	•	•	•

afford would need to be tested in different circumstances and contexts to establish what designs work in different research contexts. For now, the following hypothetical example is presented as an illustration of how this validation might work.

A Practical Worked Example for Combining Methods From Realist Inquiry and Structural Equation Modeling

The following thought experiment from our field of health professions education demonstrates how realist inquiry and SEM methods might be used in a exploratory sequential mixed method

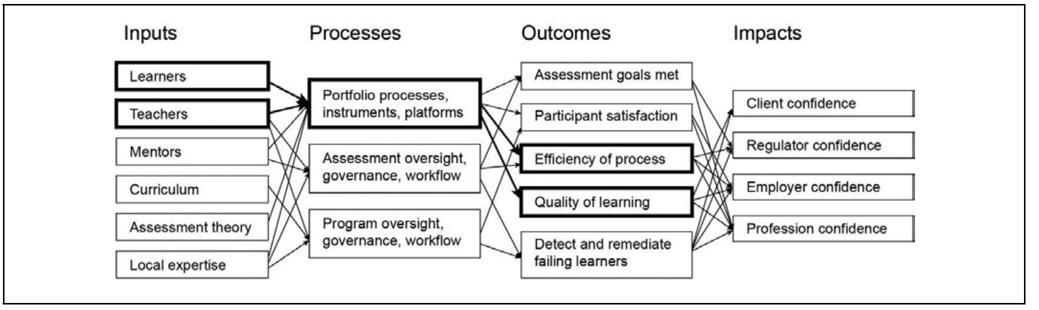

Figure 3. Preliminary program theory of the Faculty of Veterinary Medicine, Utrecht University's programmatic assessment expressed as a logic model.
Note. The elements that are later translated to the SEM stage of the study are highlighted. Note that this diagram is using the visual syntax appropriate to realist inquiry and logic models, subsequent diagrams will progressively shift to the visual syntax used in SEM diagrams.

design in order to gain a comprehensive understanding of how the program of assessment functions within its context in order to inform quality assurance and future research.

Context: Programmatic Assessment for Veterinary Medicine at Utrecht University

In 2010, the Faculty of Veterinary Medicine at Utrecht University in the Netherlands implemented a programmatic approach to assessment in their 3-year competency-based clinical curriculum (Bok et al, 2018). The program has an annual intake of 225 students and is organized around mandatory general clinical rotations and discipline-specific rotations that relate to the student's chosen track; equine health, companion animal health, or farm animal health. During their clinical rotations, students collect a variety of workplace-based assessments in a portfolio (Bok et al, 2018). The portfolio aggregates data over time and across rotations, allowing for longitudinal assessment of student progress.

Designing the Study

Our research question for this exemplar is as follows: ''In what ways do contextual factors shape the effectiveness of a program of assessment in veterinary medicine?'' A exploratory sequential design could be employed to answer this question, using realist inquiry to identify underlying contextual factors and mechanisms and create a theoretical model (a program theory), followed by SEM to test and refine a structural model of the relationships between these contextual factors and desired outcomes. The first step in this process could involve developing a logic model of how the program works in this context. To illustrate this, we developed an initial program theory based on first-hand experience, a theoretical understanding of the institution's programmatic assessment process, and iterative discussion and model building (Figure 3).

Our next step would be to select the relationships within the logic model that are to be explored and what data sources could to support this. We would then collect and analyze data in order to identify Context-Mechanism-Outcome configurations and demi-regularities, which in turn would be used to amend the initial program theory and to inform the development of structural and measurement models.

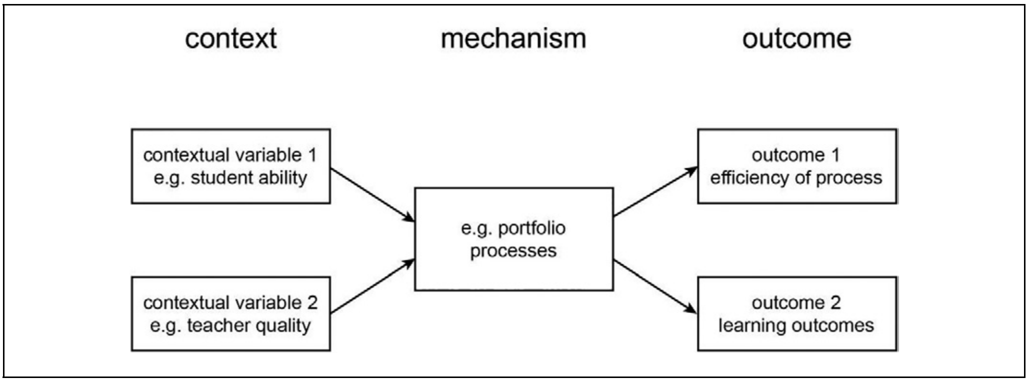

Figure 4. A Context-Mechanism-Outcome configuration extracted from the logic model in Figure 3 for translation to a path diagram.
Note. This diagram uses realist inquiry/logic model visual syntax.

Further Exploring Relationships Articulated in the Realist Program Theory Through Structural Equation Modeling Methods

The construct of outcomes in the realist program theory could then be translated to ''latent constructs'' in SEM as factors that, while they cannot be directly observed or measured, are nevertheless the result of interacting contextual variables. Contextual factors from the program theory can be represented as independent variables in SEM, and mechanisms as independent or dependent variables in SEM. We have illustrated this by taking aspects of the logic model and translating them to a path model (Figure 4).

To explore Context-Mechanism-Outcome configurations using SEM, quantitative data sources would need to be linked to the dependent and independent variables. In this case, we would use Grade Point alongside admissions data to quantify learner abilities, teacher evaluations from their learners and peers to quantify teacher quality, time and resource costs to quantify process efficiency, and exam scores and performance metrics to quantify learning outcomes (Figure 5).

Using SEM Methods to Explore How Contexts and Mechanisms Could Be Mediators or Moderators of Outcomes

Although the example in Figure 5 only presents one model specification, in practice, we would develop and test multiple model specifications. For example, a mechanism identified through realist inquiry may be specified as a mediator or a moderator variable. A mediator variable can directly generate change in another variable, whereas a moderator variable indirectly affects change in another variable by mediating the strength of the relationship between two variables. Realist mechanisms can be specified as both a mediator or a moderator variable in the initial conceptualization of the path models and once specified, goodness of fit indices can be used to inform which model better fits the data—see Figure 6.

For contextual variables, we could use means scores of learners' performance data and measures of the quality of instruction. Outcome variables could include summative evaluations and assessments of the quality of graduating students. Correlations could be explored between contextual variables and within outcome variables to examine the relationships between these latent constructs—see Figure 7.

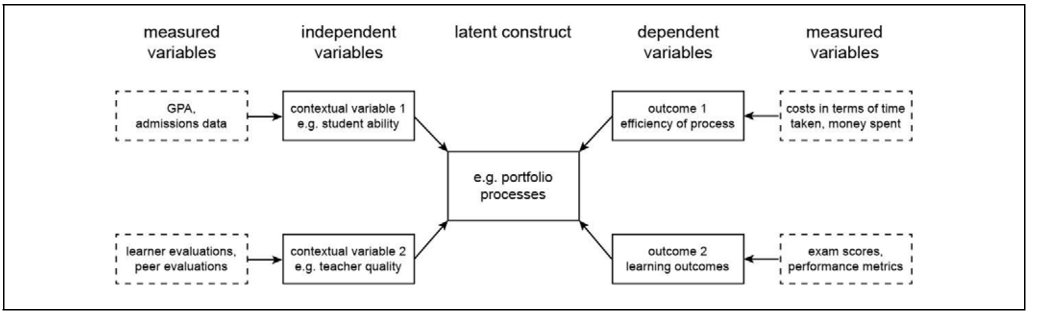

Figure 5. Transition diagram illustrating how the Context-Mechanism-Outcome configuration in Figure 4 can be expanded to serve as a structural model specification.

Note. This diagram uses a transitional visual syntax. For instance, while the convention in logic model is that time flows from left to right, the outcome variables in a path model point to the latent construct in a causal but not necessarily temporal relationship.

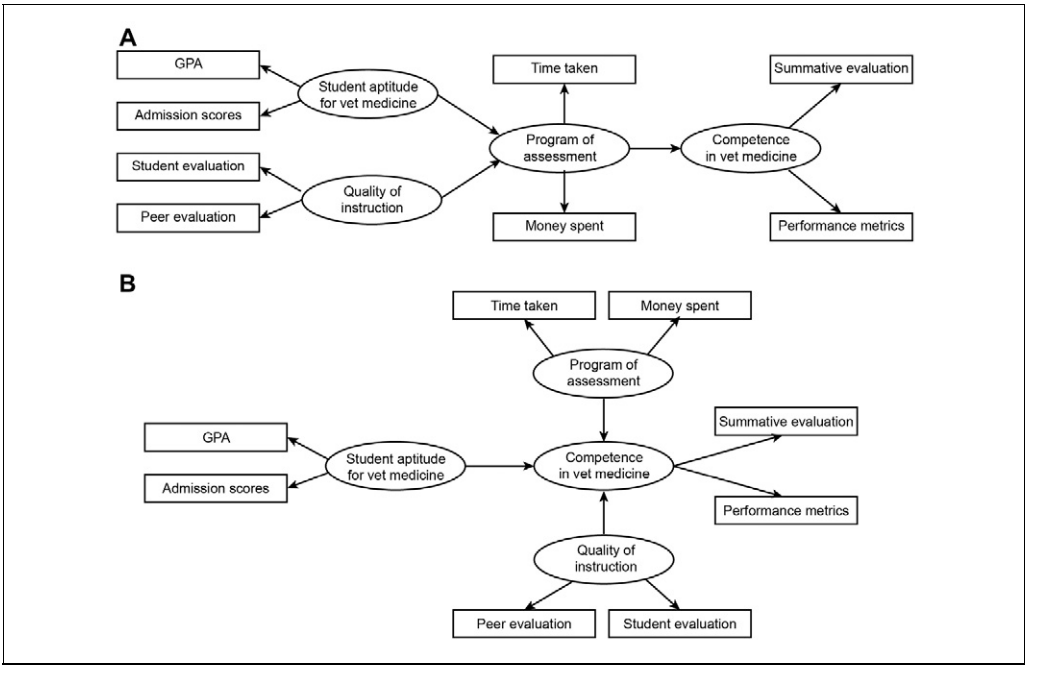

Figure 6. Two hypothetical models which propose relationships between the constructs, one with program of assessment as a mediator variable (A) and one as a moderator variable (B).

Note. These examples are now using SEM visual syntax; circles denote latent constructs; rectangles denote measurable variables.

Interpreting the Statistical Associations of the Relationships Between Contexts, Mechanisms, and Outcomes

The resulting structural model with path coefficients illustrates the relative strengths of the different relationships between contextual factors, mechanisms, and outcome. These relationships

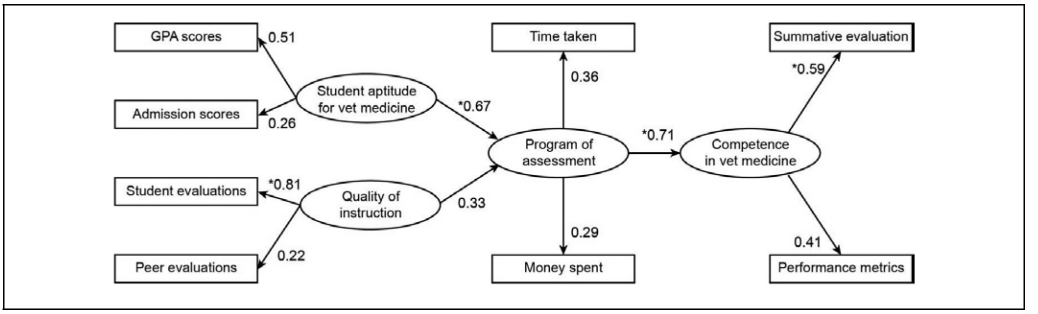

Figure 7. Hypothetical structural model derived from the path model set out in Figure 6A.
Note. The asterisk denotes which path coefficients are statistically significant. This example is also using SEM visual syntax; circles denote latent constructs; rectangles denote measurable variables.

might be further interpreted as Context-Mechanism-Outcome configurations, as the path coefficients would provide quantifications regarding which configurations are the strongest, something that current approaches to realist inquiry do not provide.

This example illustrates how methods from realist inquiry and SEM might be combined to explain how a program or system works (in this case programmatic assessment in a Dutch veterinary school). While a program may be no more measurable than a mechanism itself, researchers can measure aspects of a program or a system and build these into models that attempt to explain how and why it works.

Discussion

This article explores a number of philosophical and procedural issues in combining realist inquiry and SEM methodologies in mixed methods research. We have considered their conceptual bases, their similarities and differences, as well as different combinations of realist inquiry and SEM in mixed methods research. We considered their potential uses and limitations, which were expanded on using a hypothetical worked example.

While these two methodologies broadly fall under a postpositivist ontology, they have very different epistemological and procedural characteristics. Realist inquiry is relatively eclectic in the data it can employ (e.g., primary and secondary evidence, theory, etc.) and it generates explanatory program and middle-range theory. Procedurally, realist inquiry is abductive and focused on generative causality (how configurations of contexts and mechanisms lead to outcome regularities; Pawson, 2008). SEM on the other hand requires large samples of high-quality quantitative data to generate descriptive weighted path diagrams. Procedurally it is focused on testing and modeling ''successionist'' causalities based on interacting variables. Using realist inquiry and SEM together in a mixed methods configuration therefore requires careful translation between their respective paradigmatic spaces. There are potential limitations in doing so given their differing conceptions of rigour and validity, their orthogonal perspectives on what constitutes data, and the different symbols and syntaxes they employ. Nevertheless, the potential to generate more sophisticated evidence-based model specifications in SEM and the ability to quantify the strength and directionality of relationships between contexts, mechanism, and outcomes in realist inquiry would seem to offer much in expanding on the kinds of knowledge these approaches can generate.

This returns us to the reasons and potential benefits of combining these methodologies. realist inquiry and SEM employ different philosophies of causation (SEM works with variables, realist inquiry with mechanisms). The complementarity of these two approaches may afford particular advantages as each approach has the potential to address a fundamental limitation of the other (Maxwell, 2019). On one hand, the high-level model of causation in SEM focuses on key relationships, which might be missed in the detailed contextual explanations of realist inquiry. Similarly, realist inquiry may be able to identify specific local mechanisms acting in particular contexts that may otherwise be lost in an SEM analysis.

There is also a procedural pragmatism to combining realist inquiry and SEM, particularly in applied fields that seek to guide or effect meaningful change where the utility and effectiveness of various mixed methods research configurations have to be considered alongside their conceptual and procedural compatibility. Pragmatism (of varying kinds) is a recurring consideration in mixed methods research (Greene et al., 1989; Hathcoat & Meixner, 2017; Morgan, 2014), and such an argument does not necessarily undermine the tenets of rigour and reliability in any given methodological frame. It points to a broader social need for convergence in scientific approaches to deal with pressing problems (Gibbons, 1999). We do not claim that combining realist inquiry and SEM approaches will automatically produce more socially robust knowledge, only that the broad argument for pragmatism and convergence in science supports the argument for exploring whether and in what contexts combining these methods might do so.

Limitations and Future Directions

We acknowledge a number of limitations of this article. First, we have taken a largely deductive approach and have yet to substantially test our findings in practice. Second, we focused on pairings between realist inquiry and SEM methods and did not consider how other methods or methodologies might be added to these designs. In large part, this is because the complexity of appraising these extended designs at this conceptual level is beyond the scope of the current article, however, our team acknowledges the potential for more complex designs and the need for studies exploring their potential. Third, the worked hypothetical example was by necessity simplified to allow our research team to explore the practical challenges of combining realist inquiry and SEM; in practice there would likely be more Context-Mechanism-Outcome configurations identified and explored in SEM. In terms of next steps, clearly practical applications and appraisals will be required to substantiate our arguments. Indeed, there may be other challenges in combining these methodologies. Exploring them will require a skilled team of researchers with knowledge and expertise in both realist inquiry and SEM. To that end, we invite other scholars to explore the combination of these approaches in their work.

Contributions to the Field of Mixed Methods Research

While comparisons of realist and SEM methods have been discussed in passing (Maxwell, 2012; Pawson, 1978), this article presents an in-depth consideration and a framework for their combinations in mixed methods research. The explicit differences, but implicit similarities, between realist inquiry and SEM allow us to explore further approaches to mixing and combining methods. These combinations may be particularly useful to consider as part of evaluations that examine social interventions, such as randomized controlled trials, which often neglect to examine the potential influence that context may have on outcomes (Cartwright & Hardie, 2012). Recently, Fetters and Molina-Azorin (2020) argued for the full integration of qualitative methods within interventional studies as the *modus operandi* in order to optimize these evaluations. Strategies for conducting mixed methods randomized controlled trials have been considered as a way of providing insight into the complexities of a social intervention and to promote its transferability to other settings (O'Cathain, 2018). A key advantage of SEM methods is that they can be used to quantify causal relationships among variables (Bullock et al., 1994; Lowry & Gaskin, 2014). MMR designs involving realist inquiry and SEM could be used to identify the contexts and mechanisms that have statistical associations with outcomes of intervention studies, and ultimately, be useful in optimizing these interventions themselves. Such a design could also provide a procedural framework for conducting what are known as ''process-outcome evaluations'' that aim to understand how complex interventions work in practice (Linnan & Steckler, 2002).

This work has implications for mixed methods research in terms of implied and explicit ontological and epistemological positionings of these two approaches. By highlighting the potential intersections and combinations of these two approaches, we hope that realist inquiry and SEM will be given consideration at the outset for scholars who seek to explore causal relationships for social phenomena in multicontextual settings, that realist scientists consider the value that SEM may add to their research, and that scientists using SEM consider the advantages of using realist inquiry to guide and expand their work.

Conclusions

Realist inquiry and SEM have been independently applied in the social sciences to examine the impact of complex phenomena. Realist inquiry can answer questions surrounding how or why an intervention works, identifying contextual factors and underlying mechanisms. SEM can be used to build and test statistical models that incorporate findings from realist methods. It is argued that realism and SEM can be explicitly amalgamated into a synthetic methodology as part of mixed methods research, providing a more holistic understanding than each approach independently. This merging can result in empirically tested, refined theoretical explanations of complex phenomena. While at first glance, realism and SEM may appear to be both philosophically and methodologically incompatible, combining them in mixed methods research designs has many potential applications within the social sciences.

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