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Aligning the Qualitative Comparative Analysis (QCA) counterfactual approach with the practice of retroduction: Some preliminary insights

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Abstract

This study offers fresh ontological insights by examining generative causality through the Qualitative Comparative Analysis (QCA) counterfactual lens, in conjunction with Critical Realism and the practice of retroduction. Specifically, it claims that Information Systems (IS) researchers could retroduce generative mechanisms by leveraging the QCA counterfactual approach to causation because retroduction is about conjecturing hypothetical mechanisms that would generate the outcome of interest in a counterfactual fashion. Drawing on an example of typological theorising, this study calls for a renewed effort in the use of retroduction in the study of IS phenomena. In addition, this study sheds new light on the overarching approach for conducting Critical Realist (case study) research. A number of theoretical, methodological, and practical implications are discussed.

KEYWORDS

counterfactual approach, generative causality, mechanism, Qualitative Comparative Analysis, retroduction

"*It is important to point out that whenever researchers evaluate the logical remainders incorporated into a solution (one of the most important 'good practices' involved in using QCA), they are, in effect, deriving an intermediate solution*" (Ragin, 2009, p. 111).

1 | INTRODUCTION

This paper explores novel and interesting possibilities for understanding *counterfactual analysis* and its ontological alignment with the logic of *retroduction*. This is mainly for the benefit of information systems (IS) scholars who are interested in employing Critical Realism and/or developing innovative case study research. In particular, we focus on the potential role of Qualitative Comparative Analysis (QCA) and how commonly prescribed practices might fit the underlying principles of retroduction. The central contribution of our study is to align the QCA counterfactual approach with the logic of retroduction as practiced by Critical Realist scholars. Underpinning this contribution are a number of fresh arguments and preliminary insights. Firstly, we maintain that the synchronic or generative notion of causality, that is, the co-occurrence of the cause and the effect, entails a special mode of inference that is based on counterfactual thinking considering that the smaller the number of causal steps between the antecedent and the consequent, the more plausible counterfactual thinking will be (Fearon, 1996). Secondly, we claim that IS scholars will benefit from deploying the QCA counterfactual approach because counterfactual thinking directs IS scholars towards a non-mechanistic use of QCA techniques that enables them to engage in careful theoretical thinking about hypothetical configurations of causal conditions (Schneider & Wagemann, 2012). Thirdly, being fundamental for all retroduction (cf. Danermark et al., 2002, p. 101), counterfactual thinking calls for multiple iterations between empirical data and theoretical insights aimed at replicating the original findings either literally or theoretically. While literal replication entails solution terms that involve similar or, in the extreme, identical necessary and sufficient conditions, theoretical replication entails no such thing and, therefore, calls for theorising new mechanisms that warrant different substantive interpretations of the empirical data at hand.

Drawing on a running example of typological theorising (Iannacci & Cornford, 2018), we show that there is a natural fit between the Critical Realist paradigm and QCA because they both advocate methodological and theoretical pluralism (Danermark et al., 2002; Mingers et al., 2013; Park et al., 2020; Schneider & Wagemann, 2012; Wynn & Williams, 2012). Not only is QCA "inherently a multi-method approach" (Schneider & Wagemann, 2012, p. 319) but it also endorses theoretical and configurational multiplicity, that is, "the applicability of multiple theoretical perspectives," as well as "the existence of multiple configurations of relevant factors for a given theoretical perspective" (Park et al., 2020, p. 1494), thus aligning with the Critical Realist cardinal principle of theoretical and methodological pluralism (cf. Danermark et al., 2002, pp. 150–176; Wynn & Williams, 2012, p. 803). Furthermore, both QCA and Critical Realism rest on a solid template that begins with the analysis of the outcome of interest and postulates plausible causal mechanisms in a retroductive fashion (Ragin, 1994). Indeed, conceptual progress is more likely when retroduction revolves around counterfactual thinking because it works *holistically* towards the formulation of a plurality of hypothetical mechanisms that could carry the explanatory burden. The analyst's task is then to *eliminate* the least plausible mechanisms and *identify* more parsimonious configurations of causal conditions that *correct* existing knowledge so as to articulate inferences to the "best" explanation (Lipton, 2004).

The paper is structured as follows. After calling for a renewed effort in the use of retroduction in general and the QCA counterfactual approach in particular, we discuss difference-making and production accounts of causality in Section 2 to outline two broad approaches for the study of synchronic (or generative) and diachronic (or event) causality respectively. Section 3 gives an overview of Critical Realism as an underpinning ontology for QCA while Section 4 develops some preliminary insights into the quest for synchronic (or generative) mechanisms. Section 5 discusses the core theoretical, methodological, and practical implications of this paper, and Section 6 concludes the paper. Finally, the Appendix draws on practical examples to show how the retroduction logic may inform large-N QCA studies (see Park et al.'s, 2017 example), as well as multiple simplifications at once (see Ragin & Sonnett's, 2005 example). The Appendix also "intentionally complexifies" (Cornelissen et al., 2021, p. 8) the Iannacci and Cornford's (2018) study to show how to run a robustness test and arrive at an empirical range that warrants the same substantive interpretation of the empirical data.

2 | DIFFERENCE-MAKING ACCOUNTS VERSUS PRODUCTION ACCOUNTS OF CAUSALITY

The concept of retroduction is very difficult to pin down because it is about discovering causal mechanisms that are extremely challenging to define. Though scholars have provided a wide range of definitions of mechanisms (e.g., Gerring, 2008; Hedström & Swedberg, 1998; Hedström & Ylikoski, 2010; Illari & Williamson, 2012; Mahoney, 2001; Markus & Rowe, 2018; Mingers, 2014; Mingers & Standing, 2017), mechanisms are deeply intertwined with the notion of causation. Indeed, causation and, indirectly, causal mechanisms can be approached from two vantage points, namely, production and difference-making accounts (Illari & Russo, 2014). While production accounts focus on the temporal process whereby the cause brings about the effect, difference-making accounts establish the causal relationship between cause and effect by looking at whether the occurrence or non-occurrence of the cause makes a difference to the occurrence or non-occurrence of the effect (Ibid). Another way of distinguishing between these two types of causality is to draw on Mingers and Standing's (2017) notion of diachronic (or event) causality and generative (or synchronic) causality, the former looking at the causal connection between events *over time*, the latter explaining the emergence of events *at the same time*.

Likewise, Goertz and Mahoney (2012) have outlined two distinct approaches to the study of causality, namely, the effect-of-causes and causes-of-effect accounts. The former approach looks at the effects of a potential cause on the outcome of interest while the latter approach works backward by tracing the actual causes that are individually necessary and jointly sufficient for the outcome of interest. Somehow mirroring the distinction between variance and process theories (Burton-Jones et al., 2015; El Sawy et al., 2010; Markus & Robey, 1988; Mohr, 1982; Seddon, 1997), the effects-of-causes approach focuses on the "net-effects" (or "average effects") of causal conditions conceptualised as variables whereas the causes-of-effects approach looks at causes conceptualised as (binary) events that, in a certain sequence, lead to the outcome of interest. Put in variance-and-process terms, variance theories "assert that, for some population of interest, if all other things are equal, variance in any one of the independent variables is necessary and sufficient to cause variance in the dependent variables" (Seddon, 1997, p. 241). On the contrary, process theories "show how certain combinations of events, in a particular sequence, cause certain outcomes" and, therefore, "each event, in the process is necessary but not sufficient to cause the outcome" (Ibid: 241). Far from being two distinct epistemological claims about different ways of theorising IS phenomena, variance and process theories are rooted in different views about the nature of causality (or "causal ontology") considering that these two positions "differ fundamentally on the question of whether causality is relevant only in a single case (i.e., process theory) or only to an entire population of similar entities (i.e., variance theories)" (Markus & Rowe, 2018, p. 1273).

Though variance and process theories have dominated IS research, more recently the systems perspective has re-emerged within IS studies (Burton-Jones et al., 2015). This perspective "focuses on wholes, parts, and emergent properties that arise from interactions among parts" (Ibid: 668). The systems perspective views IS phenomena as clusters of interconnected elements (or causal conditions) that generate holistic effects *simultaneously*. It accommodates complex interconnections of multiple elements (or causal conditions) such as "suppression, substitution, and complementary effects" (El Sawy et al., 2010, pp. 839–844). Hence, it views mechanisms as systems of interacting parts, that is, as assemblies of elements (or causal conditions) generating "an effect not inherent in any one of them" (Hernes, 1998, p. 74).

In what follows, we argue that IS scholars will benefit from using set-theoretic methods in general and the QCA counterfactual approach in particular and that difference-making is the unifying principle for set-theoretic, multi-methods research (Rohlfing & Schneider, 2018). Specifically, we argue that using these new methodological approaches and techniques allows IS scholars to account for differences among instances of a certain phenomenon (Ragin, 1987) and that the QCA counterfactual approach is especially geared to retroducing synchronic mechanisms. Ultimately, we argue that the QCA counterfactual approach sheds new light on retroduction because it is premised on the assumption that a hypothetical configuration of causal conditions "only qualifies as causal when it makes a difference to the outcome" (Rohlfing & Schneider, 2018, p. 46). This means shifting the focus from a diachronic view of causality to a synchronic or generative view where entities have an immediate effect on other entities "through interconnecting circuits of software that makes them uniquely addressable and consistently machine-readable, and thus exposed to external processes of identification and linkage that embeds them in the emerging 'Internet of Things'" (Kitchin & Dodge, 2011, p. 47).

3 | CRITICAL REALISM AS AN UNDERPINNING ONTOLOGY FOR QCA

Mahoney (2001) has made a compelling argument for moving beyond correlational analysis using the set-theoretic logic of QCA. More recently, Rutten (2021) has endeavoured to connect QCA with Critical Realism. In particular, according to Rutten (2021), QCA can be connected to the three domains of the Real (i.e., underlying mechanisms), the Actual (i.e., events and non-events) and the Empirical (i.e., events that are either experienced or observed). According to Rutten (2021), QCA is committed to Critical Realism as "causal inference is a matter of substantively interpreting empirical findings (complex solutions with consistent set-subset relationships) and knowledge of cases and context into plausible explanations" (Ibid: 4). This, in turn, calls for a movement from the Empirical domain where outcomes can be either observed or experienced to the Real domain of mechanisms through the Actual domain of events (and non-events). Figure 1 below depicts the retroduction logic when QCA is informed by the Critical Realist ontology (i.e., the three domains of the Real).

Far from being a formulaic exercise in truth-table minimization where analysts include truth-table rows in the minimization process using decontextualized frequency and consistency thresholds (Greckhamer et al., 2013), QCA entails a back-and-forth cycling between "empirical, substantive and theoretical knowledge" resulting in "recalibrations and setting different (frequency and consistency) thresholds in the truth table" (Rutten, 2022, p. 1214). This, in turn, calls for continuous refinement of the truth table as "it requires in-depth knowledge of cases and many iterations between theory, cases, and truth table construction" (Ragin, 2008, p. 25). Accordingly, decontextualized frequency and consistency thresholds cannot be taken as evidence of causal relations. Rather, they should be seen as simple cross-case, empirical regularities that mask the presence of unobservable mechanisms. The

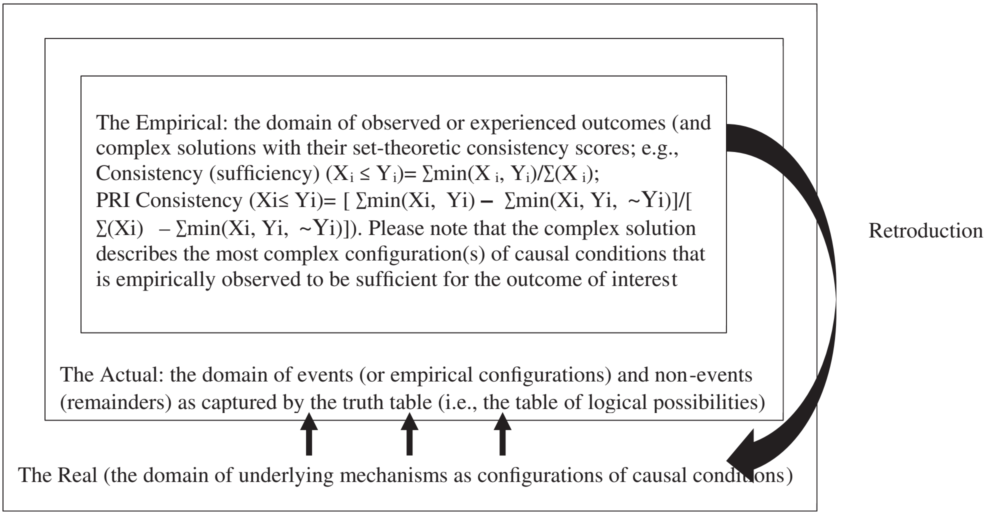


FIGURE 1 The retroduction logic when Qualitative Comparative Analysis is informed by the Critical Realist ontology (adapted from Mingers, 2004, Mingers et al., 2013, as well as Rutten, 2021)

analyst's task, therefore, is to move beyond the empirical domain by hypothesizing plausible mechanisms that could generate the observed outcomes in an ongoing, back-and-forth fashion.[1]

The QCA counterfactual approach can help analysts in their search for generative (or synchronic) mechanisms considering that it can help them formulate counterfactuals that are theoretically and logically consistent with existing knowledge (Soda & Furnari, 2012). By looking at remainders in the truth-table rows, analysts can draw on their theoretical and substantive knowledge of the cases at hand to formulate directional expectations about the effects of single conditions or conjunctions of conditions on the outcome of interest. By claiming that such logical remainders are sufficient for the outcome of interest in line with their directional expectations, analysts can simplify their complex solutions counterfactually (Schneider & Wagemann, 2012). Indeed, QCA strongly encourages analysts to assess the status of their simplifying assumptions “about combinations of conditions that lack empirical instances. In QCA, these assumptions must be evaluated” (Ragin, 2008, p. 157). Ultimately, when QCA is underpinned by the Critical Realist ontology, QCA scholars espouse “a *causal* criterion for existence rather than a perceptual one” (Mingers et al., 2013, p. 796; italics in original) because they attempt to discover what the effects of underlying mechanisms would look like if they were actualised through specific configurations or combinations of causal conditions. Crucially, such QCA scholars should use a retroductive mode of thinking to move from their knowledge of empirical phenomena as expressed through consistent set-subset relationships “to the creation of explanations (or hypothesizing) in ways that hold “ontological depth” and can potentially give some indications on the existence of unobservable entities (or mechanisms)” (Zachariadis et al., 2013, p. 858).

4 | PRELIMINARY INSIGHTS ON RETRODUCTION AND SYNCHRONIC MECHANISMS

Above, we have argued that one way to shed new light on the retroduction process is to draw on the QCA counterfactual approach.[2] This approach invite IS scholars to formulate causal inferences premised on a difference-making account of causality and the formulation of explanations in terms of generative (or synchronic) mechanisms conceived of as INUS configurations. We now use a running example based on Iannacci and Cornford's (2018) recent study to develop preliminary insights on retroductive thinking. We also take stock of recent IS scholarship using QCA (or one of its variants such as fuzzy-sets or crisp-sets) to *identify* causal mechanisms and *correct* existing knowledge in the IS field. Iannacci and Cornford (2018) study was selected for four reasons: first, it uses in-depth case knowledge for the calibration (or scoring) of qualitative data (De Block & Vis, 2019); second, in spite of its small sample, it scores cases using fuzzy sets rather than crisp sets, thus heeding Ragin's (2008, p. 141) advice that researchers should not use crisp sets if they “can represent their causal conditions and outcomes as fuzzy sets”; third, it uses QCA techniques in a multi-methods fashion because “findings generated by QCA as a technique alone are less convincing than those that are followed by other analyses, most likely, but not exclusively, within-case studies of cases identified as typical and deviant by the QCA” (Schneider & Wagemann, 2012, p. 282); fourth, and last, it deals with a surprising anomaly, namely that manual validation of monitoring data generated positive downstream outcomes. Accordingly, this study nicely sets the stage for a retroductive mode of thinking aimed at discovering or perhaps conjecturing hypothetical mechanisms that could dissolve the anomaly in a counterfactual fashion (Mingers, 2014; Sætre & Van de Ven, 2021).

In their recent study, Park et al. (2017) have explicitly used the word “retroduction” to refer to an iterative dialogue between theoretical ideas and empirical evidence (Ibid: 657). Drawing on the idea that there is a fundamental mismatch between methods and theories in the social sciences (Fiss, 2007), they have called for a paradigm shift. Specifically, they have called for a QCA set-theoretic approach to bypass the assumptions of singular causation and linear relations. Accordingly, Park et al. (2017) have issued a call for meta-retroduction to ensure a closer fit (or alignment) between the empirical study of organisational configurations and the methodological assumptions of QCA. Park et al. (2017) have explicitly advocated that QCA reasoning is both deductive and inductive. It is deductive because causal relations are informed by prior theory. It is inductive because calibration (i.e., the scoring of causal conditions) revolves around the substantive knowledge of the empirical cases at hand (Ibid). Yet, Park et al. (2017) did not discuss how their retroductive reasoning relates to causal mechanisms.

Fiss (2011), however, has made a strong case for showing the utility of the QCA approach in developing the theory of causal mechanisms in organisations. Challenging the assumption that "all parts of the configuration are equally necessary or important" (Ibid: 396), Fiss (2011) has come up with "a definition of coreness based on which elements are causally connected to a specific outcome" (Ibid: 398). More specifically, he defined "core elements as those causal conditions for which the evidence indicates a strong causal relationship with the outcome of interest. In contrast, peripheral elements are those for which the evidence for a causal relationship with the outcome is weak." (Ibid: 398). Since Fiss' (2011) argument revolves around a "regularity theory" of causation (cf. Rutten, 2021, p. 8) and since "core" conditions may or may not include necessary conditions, Iannacci and Cornford (2018) have provided a different perspective that draws on Critical Realist principles. Critical Realist scholars do not assume that a parsimonious solution is the very "core" of their causal argument. Though this solution is normally associated with a larger coverage score, coverage (sufficiency) is merely an indicator of empirical importance (Ragin, 2006). For a Critical Realist scholar, a necessary condition should be at the "core" of the causal argument. Accordingly, Iannacci and Cornford (2018) distinguished between core (i.e., necessary) and peripheral (i.e., contingent) conditions depending on their theoretical (not empirical) importance. By so doing, Iannacci and Cornford (2018) have defined "coreness" based on the strength of the causal argument rather than the strength of the evidence for the causal argument (cf. Park et al., 2020, p. 1499).[3]

4.1 | Connecting the QCA counterfactual approach with the Critical Realist methodology

Leveraging the insight that the QCA counterfactual approach can be used as a paradigm shift for developing a theory of causal mechanisms in general and retroductive thinking in particular (Rutten, 2021), we now suggest how one could apply the QCA approach as a methodology for theoretical and empirical research. It is important to reiterate that this approach fits the Critical Realist paradigm (Wynn and Williams, Wynn & Williams, 2020, p. 64) because QCA shares many commonalities with this paradigm (Gerrits & Verweij, 2013; Gerrits & Pagliarin, 2020; Henfridsson & Bygstad, 2013; Rutten, 2022; Steinmetz, 1998; Tóth et al., 2017). For example, using Critical Realism as their underpinning paradigm, Tóth et al. (2017) argue that the "holistic view about the interdependency of conditions fits well with the configurational approach of fuzzy-set QCA" (Ibid: 194). As such, their study "looks at the causal conditions, including their interplay, as parts of a 'given' reality, and allows for a more exploratory view of the relationships between them, as well as their effect on specific outcomes" (Ibid: 194). Likewise, in his assessment of large-N QCA, Rutten (2022) advocates a substantive interpretation of QCA findings that connects seamlessly to Critical Realism and its notion of causality as generative causality, that is, causal mechanisms that "imply interaction of multiple individual causes" (Ibid: 1217). "Critically, cross-case regularities (consistent set-subset relationships) are not themselves causal mechanisms; they are empirical manifestations of underlying causal mechanisms that must be interpreted into statements of sufficiency by going back to the cases" (Ibid: 1216; see also Gerrits & Verweij, 2013, p. 176).

The methodology at the core of Critical Realist studies consists of five steps, namely Description, Retroduction, Elimination, Identification, and Correction (aptly captured with the DREIC acronym). Since retroduction aims at conjecturing hypothetical mechanisms that could generate the observed outcomes, retroduction switches the focus away from theory testing and probabilistic explanation to theory building and possibilistic explanation. Nevertheless, there are very few theoretical and empirical applications of the retroduction logic within mixed-methods and multi-methods studies (Zachariadis et al., 2013). We contend that IS scholars can leverage the QCA counterfactual approach within mixed-methods and multi-methods studies to apply the DREIC approach in general and the retroduction logic in particular. Hence, we now set out to connect the QCA counterfactual approach to causation with the Critical Realist DREIC methodology for theoretical and empirical research.

The first step in QCA consists of breaking down the cases at hand in terms of theoretically relevant configurations using the principle of theoretical and configurational multiplicity (Park et al., 2020). Accordingly, based on an in-depth analysis of relevant literature, one can *describe* these cases as set-theoretic configurations of causal conditions. Once cases are conceptualised as theoretically relevant packages, one can proceed with their calibration by scoring cases' set membership using an iterative dialogue between theory and empirical evidence (Ragin, 2000). Calibration enables scholars to locate cases in those configurations where their membership is greater than 0.5. At this stage, the analyst can achieve a more fine-grained *description* of the cases by producing a truth table, that is, a table that lists all logically possible combinations of causal conditions both present and absent with their associated outcomes (Schneider & Wagemann, 2012). A truth table has 2^k rows where K is the number of causal conditions. The empirical cases can then be assigned to these rows on the basis of their values for the causal conditions, with some rows containing many cases, some rows just a few, and some rows containing no cases at all.[4]

The second step uses counterfactual analysis as a *retroductive* strategy to propose hypothetical recipes (or causal configurations) that, *if they existed*, would lead to the outcome of interest (Mingers, 2004). Essentially, at this stage, the analyst must decide whether to bar all empty rows (or potential counterfactuals) from the analysis or include a few remainder rows for counterfactual analysis. Ragin (2008) distinguishes between "easy" and "difficult" counterfactuals depending on whether they are in line with theoretical and substantive knowledge. By being consistent with existing knowledge, "easy" counterfactuals are more exacting than "difficult" counterfactuals and, therefore, they only enable a fraction of the pool of remainders for analysis. Conversely, "difficult" counterfactuals may not align with theory-guided hunches. As a methodology for theoretical and empirical research, QCA allows for three solutions, that is, three distinct statements about one or multiple combinations of causal conditions that are jointly sufficient for the outcome of interest. Complex solutions occur when analysts bar all counterfactuals from their analysis. Instead, intermediate and parsimonious solutions entail the inclusion of "easy," as well as "easy" and "difficult" counterfactuals respectively. Since the incorporation of counterfactuals produces simpler or shorter solutions, it follows that complex solutions are a subset of intermediate solutions which, in turn, are a subset of parsimonious solutions where all counterfactuals are incorporated regardless of whether they are "easy" or "difficult." Furthermore, these counterfactuals need not be limited to the analysis of single conditions in isolation, but they could be extended to expectations that researchers have "about the effect of *combinations* of conditions on the outcome" (Schneider & Wagemann, 2012, p. 215; italics in original).

To further clarify the retroduction logic, the empirical study of Iannacci and Cornford (2018) can be considered wherein they investigated causal configurations of positive impact in the context of the European Social Fund. They discovered two configurations sufficient for positive impact. Both of these configurations exhibited common factors (or necessary conditions) in terms of Compatibility, Comprehensiveness, Currency AND Reliability. However, one configuration was characterised by automated monitoring systems whereas the other configuration exhibited manual systems that leveraged the presence of a consistent set of indicators thanks to the "four-eye" principle (that is, two people looking at the same data set to ensure information quality). These two solutions are displayed in Figure 2 below along the parsimony-complexity continuum:

With the presence of six conditions (k = 6), their truth table (or table of logical possibilities) featured 2^6 rows (that is, 64 rows). Nevertheless, only a fraction of these rows was populated with cases because of the small N.[5]

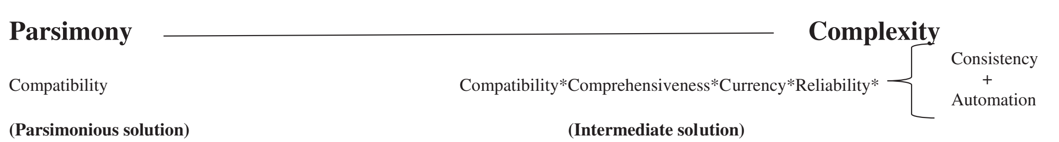
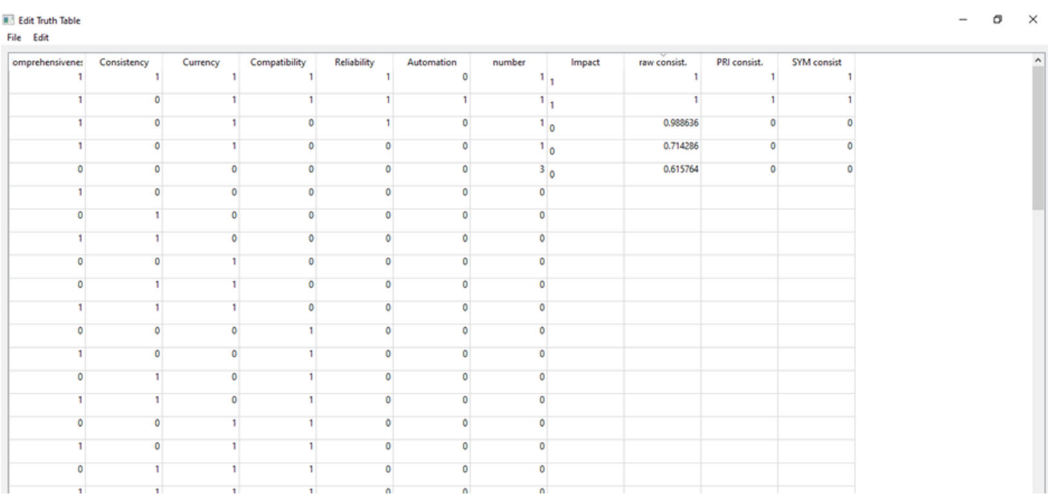


FIGURE 2 The parsimony-complexity continuum (Legend: * = Logical AND; + = Logical OR)

More specifically, from a pool of 64 possible combinations of causal conditions, only 5 rows were populated with empirically strong cases. Figure 3 displays Iannacci and Cornford's (2018) truth table:

Accordingly, Iannacci and Cornford (2018) had to speculate about the outcome of these empty truth-table rows by proposing hypothetical configurations (or INUS configurations) that, *if they existed*, would generate or cause the outcome of interest. At this juncture, Iannacci and Cornford (2018) could have included in their solution either easy counterfactuals only or both "easy" and "difficult" counterfactuals regardless of their theoretical plausibility. If they had pursued the latter strategy, these scholars would have included a pool of 30 simplifying assumptions generating the most parsimonious solution, namely, Compatibility. Figure 4 below displays the pool of simplifying assumptions that the most parsimonious solution would have incorporated[6]:

The third step consists of *eliminating* alternative competing hypotheses (Mingers & Standing, 2017). This step is related to step two when using QCA and mimics the process of running multiple thought trials (Weick, 1989) where the analyst retains the theoretically plausible counterfactuals but discards those counterfactuals that are theoretically implausible. Let us return to Iannacci and Cornford (2018) study. As stated above, these researchers had a large pool of remainders (or potential counterfactuals) considering that only 5 truth-table rows were populated with empirically strong cases. Potentially, all empty truth-table rows were candidates for the outcome of interest. Accordingly, Iannacci and Cornford (2018) had to decide whether to incorporate empty rows in their analysis regardless of whether they entail "easy" and "difficult" simplifying assumptions or, more simply, allow for the incorporation of "easy" counterfactuals only. Though the incorporation of "easy" counterfactuals leads to a more conservative solution (labelled the "Intermediate" solution in the QCA terminology), this solution effectively bars difficult counterfactuals from the analysis, thus *eliminating* alternative competing mechanisms. By formulating conjunctural directional expectations about the outcome of these hypothetical configurations, Iannacci and Cornford (2018) pinpointed one and only one plausible configuration from a pool of 30 simplifying assumptions, namely, the configuration entailing the presence of each and every component part. Compared with the other potential simplifying assumptions, this is the only configuration that is neither incoherent nor questionable.[7] This configuration, in turn, may be regarded as a



omprehensivene:	Consistency	Currency	Compatibility	Reliability	Automation	number	Impact	raw consist.	PRI consist.	SYM consist
1	1	1	1	1	0	1	1	1	1	1
1	0	1	1	1	1	1	1	1	1	1
1	0	1	0	1	0	1	0	0.988636	0	0
1	0	1	0	0	0	1	0	0.714286	0	0
0	0	0	0	0	0	3	0	0.615764	0	0
1	0	0	0	0	0	0				
0	1	0	0	0	0	0				
1	1	0	0	0	0	0				
0	0	1	0	0	0	0				
0	1	1	0	0	0	0				
1	1	1	0	0	0	0				
0	0	0	1	0	0	0				
1	0	0	1	0	0	0				
0	1	0	1	0	0	0				
1	1	0	1	0	0	0				
0	0	1	1	0	0	0				
1	0	1	1	0	0	0				
0	1	1	1	0	0	0				
1	1	1	1	0	0	0				

FIGURE 3 Truth Table (Legend: 0 = absent condition; 1 = present condition, but under the impact column 0 stands for not consistent and 1 for consistent meaning that the configuration in question is either a consistent subset of the outcome (1) or not (0); raw consistency = degree to which the combination of causal conditions is a subset of the outcome—the default way of assessing consistency; PRI consistency = proportional reduction in inconsistency—a more stringent parameter to interpret set-theoretic relations; SYM consistency = symmetry consistency—a tweaked version of PRI consistency used to study both positive and negative cases; remainders = rows with zero number of cases or empty truth-table rows/potential counterfactuals)

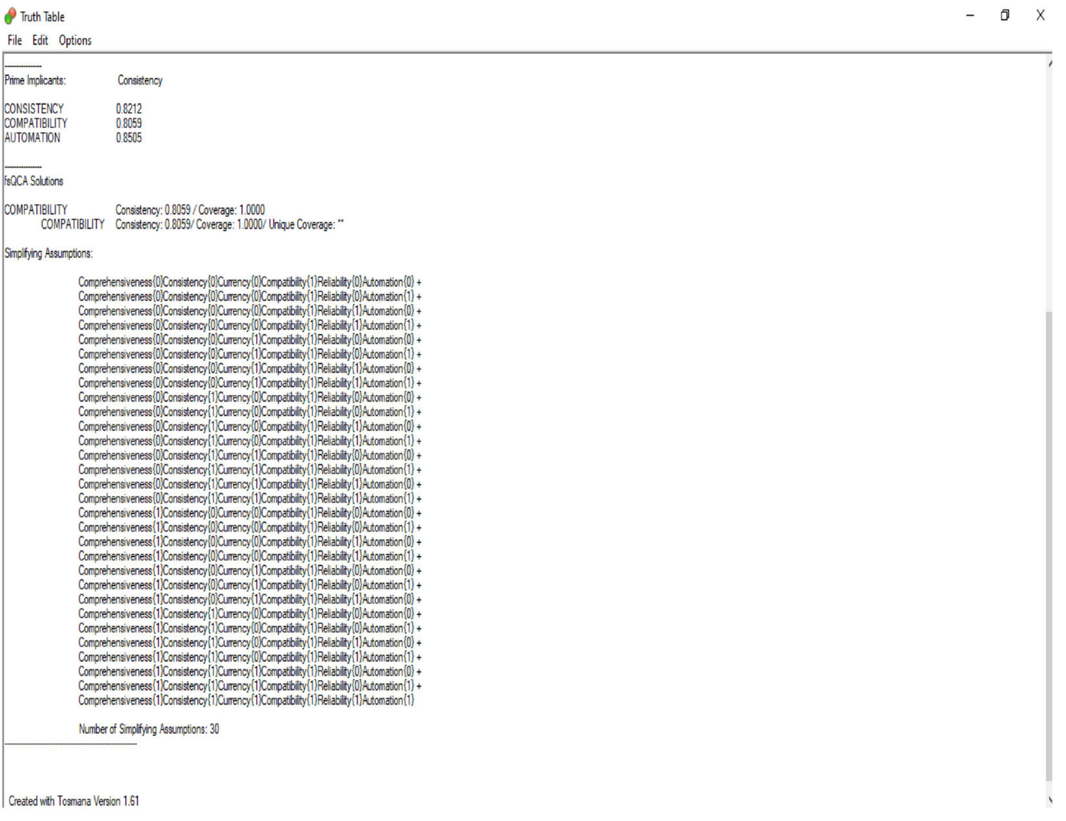


FIGURE 4 The pool of simplifying assumptions generating the most parsimonious solution (Legend: 1 = present; 0 = absent; + = Logical OR; blank space = Logical AND)

"synthetic" counterfactual case which is then compared with the empirically strong cases (Abadie et al., 2015). Table 1 shows the simplification process that Iannacci and Cornford (2018) have implicitly applied using the fsQCA software programme (Ragin & Davey, 2016), thus removing a redundant causal condition that, whether present or absent, does "not make a difference to the outcome" (Rohlfing & Schneider, 2018, p. 50). Hence, the "synthetic" counterfactual invokes the difference-making approach with the "primary goal of *confirmation*" (Ibid; italics in original).

In the fourth step, analysts must *identify* the correct mechanism by "going back to the cases" (Rutten, 2022, p. 1216). For example, Iannacci and Cornford (2018) *identified* two mechanisms that are jointly sufficient for positive impact. Specifically, they have argued that the achievement of an efficient and effective monitoring process requires monitoring systems that collect a comprehensive and up-to-date range of indicators and that depend on reliable technologies with compatible communication protocols. Though this bundle of conditions lies at the core of their mechanisms, Iannacci and Cornford (2018) *identified* more contingent (or peripheral) conditions depending on whether the monitoring system is fully automated or, alternatively, is still relying on manual checks, but based on consistent definitions of monitoring data. While in one context (see Austria in Table 1) the use of a consistent set of monitoring data compensated for the lack of automated checks thanks to the use of the "four-eye" principle (i.e., that is, two people looking at the same data set), it turned out that in a different set of contextual contingencies (see Germany in Table 1) the Compatibility of the monitoring system counteracted the lack of Consistency among monitoring data thanks to the exchange of structured data across interfaces (cf. Iannacci & Cornford, 2018, p. 402). Accordingly, Iannacci and Cornford (2018) argued that these counteracting mechanisms are what make distinct

TABLE 1 Inclusion of "easy" counterfactuals to arrive at the intermediate solution

Country	COMPR*cons*CUR*COMPT*REL*AUT	COMPR*CONS*CUR*COMPT*REL*aut	COMPR*CONS*CUR*COMPT*REL*AUT (Easy counterfactual)
Austria	0.00	**0.51**	0.49
England	0.25	0.25	0.25
Flanders	0.49	0.25	0.25
France	0.25	0.25	0.25
Germany	**0.75**	0.25	0.25
Greece	0.00	0.25	0.25
Hungary	0.49	0.25	0.25

COMPR*CUR*COMPT*REL*AUT

COMPR*CONS*CUR*COMPT*REL

Note: COMPR = Comprehensiveness; CONS = Consistency; CUR = Currency; COMPT = Compatibility; REL = Reliability; AUT = Automation. Lower case = absence; Upper case = presence (cases with strong membership in the configuration are represented in bold).

configurations "tick" across different contingencies (Bunge, 1997). Likewise, Henfridsson and Bygstad (2013) *identified* two mechanisms for the successful evolution of digital infrastructures, namely one where "the innovation mechanism should be targeted as the (key) driver" (Ibid: 927) and one lacking such a key driver of change. While the innovation mechanism in conjunction with adoption and scaling was contingent on a loosely coupled architecture and decentralised control, the lack of innovation had "no specific relationship between mode of control and architecture" (Ibid: 926) in those successful cases combining adoption and scaling. Therefore, in this fourth step, IS scholars can *identify* synchronic mechanisms as configurations of causal conditions that are individually necessary and jointly sufficient for the outcome of interest (Mackie, 1965).

In the fifth and final step, IS scholars will *correct* scientific knowledge in light of their (provisional) findings (Mingers & Standing, 2017). In the given example, Iannacci and Cornford (2018) have reappraised the causal and temporal influences underpinning the DeLone and McLean's IS success model in the European Social Fund context (DeLone & McLean, 1992) and developed a typological theory of IS success revolving around contingent generalisations about configurations of conditions that constitute theoretical types (George & Bennett, 2005). On their part, Park et al. (2017) have reinvigorated a contingency-theory approach in the study of organisational agility. More specifically, they have highlighted the role that Business Intelligence tools and Communication Technologies play in achieving organisational agility in different organisational and environmental contexts.

5 | DISCUSSION

The use of QCA techniques can help IS scholars switch their mode of inference towards more intensive use of retroduction in general and counterfactual thinking in particular. This shift, in turn, is beneficial for a variety of reasons. First, despite claims to the contrary (Bergene, 2007), it sheds new light on the DREIC approach for conducting Critical Realist (case study) research because it shows that counterfactual thinking is a fundamental step in the DREIC approach for theoretical and empirical research. Second, it enables IS scholars to conceptualise synchronic mechanisms as configurations of causal conditions. Since each configuration is an unnecessary package for the outcome of interest, it follows that "a certain effect can be brought about by a number of distinct clusters of factors: each of the clusters is sufficient to bring about the effect, but none of them is necessary" (de Guinea & Webster, 2017, p. 150). Third, and relatedly, for each effect, there is a plurality of causal configurations (Ibid). Accordingly, IS scholars can discover multiple recipes for the outcome of interest, thus laying out the foundation for the development of configurational theories, that is, contingent generalisations about configurations of conditions that bring about outcomes jointly and synergistically (El Sawy et al., 2010). This, in turn, will help to address the recent call for multi-causal explanation in IS research (Avgerou, 2013). It could also help IS scholars in their quest for explanatory pluralism (Hovorka et al., 2008) because the counterfactual approach in QCA is "possibilistic in nature rather than probabilistic" (Rutten, 2022, p. 1217). In other words, QCA adds configurational relevance to the four explanation types identified by Hovorka et al. (2008). Compared with statistical relevance which looks at the interaction of a "large number of causal factors" on the basis of "hypothesis testing and probabilistic explanation" (Ibid: 30), the QCA approach "models possibilistic uncertainty in that logical remainder rows, for which it is uncertain whether the outcome is possible, are turned into easy and difficult counterfactuals depending on their plausibility" (Rutten, 2022, p. 1217). Hence, QCA switches the focus to theory building and possibilistic explanation, as well as to interactions between and among interdependent causal conditions that "can be complementary, substituting, or suppressing in nature" (Park & Mithas, 2020, p. 88; footnote 7). This, in turn, lays the foundation for configurational causality, that is, a new type of causality that is "configurational rather than additive, equifinal rather than unifinal, and asymmetrical rather than symmetrical" (Rutten, 2019, p. 13). Fourth, and last, such configurations are not expected to involve the same conditions in each instance of the outcome of interest nor are they expected to have the same effect on the outcome regardless of other conditions. Rather, they work in conjunction with each other, thus generating holistic effects not inherent in their individual parts (Mahoney, 2001).

The epistemic aim of science is to explain phenomena and "this is precisely what mechanisms provide" (Hedström & Ylikoski, 2010, p. 54). Yet, as a socio-technical discipline, the IS field has mostly looked at mechanisms diachronically. Whether using Archer's (1995) morphogenetic approach, DeLanda's (2006) theory of assemblages or Pawson and Tilley's (1997) realistic evaluation framework, IS scholars have drawn on the notion of diachronic causality and, therefore, on production accounts of causality looking at the temporal process whereby the cause brings about the effect (Illari & Russo, 2014). Accordingly, IS scholars have implicitly conceptualised mechanisms as "entities (e.g., IT artefacts) and activities (e.g., digitisation processes) organized in such a way that they are responsible for the phenomenon" under investigation (e.g., technological change). For example, drawing on DeLanda (2006), Bygstad (2010) has discovered a double set of self-reinforcing mechanisms underpinning the evolution of a complex service-oriented IT architecture. Specifically, he argued for the operation of both innovation mechanisms and service mechanisms that recursively feed on themselves *over time*.

More recently, drawing on Norman's (1988) affordance lens, IS scholars have conceptualised mechanisms as possibilities for action that can be actualised through the design of IT artefacts (Volkoff & Strong, 2013). The actualisation of affordances, in turn, explains organisational and technological change through morphogenetic cycles of macro structures conditioning individual actions which then lead to subsequent reproduction or transformation of pre-existing structures.[8] Nevertheless, production accounts of causality provide just one way of looking at causality (i.e., the diachronic view of causality). "Smart technologies" can trigger near-real time outcomes without continuous human intervention (Markus & Rowe, 2018). Indeed, even "contemporary forms of Artificial Intelligence (AI) have an increasing capacity to act on their own, without human intervention" (Berente et al., 2021, p. 1436). Such near-real time outcomes call for a different conceptualisation of causality altogether, namely a synchronic or generative view of causality revolving around a difference-making account rather than a production account (Illari & Russo, 2014). "Importantly, this means that a time-sequence between cause and outcome is not necessary for causality and that the need for a time-sequence is specific for the empiricist notion of causality" (Rutten, 2019, p. 5).

For example, on Friday 7 October 2016, Sterling fell sharply overnight because algorithms feeding off news headlines and other social media platforms "set off a vicious circle in which the Pound's slump became a self-fulfilling prophecy" (The Guardian, 2016). This near-real time plunge in Sterling happened "within a few minutes" because of the action of algorithmic trades setting off the trade signals of other algorithms when asset prices fell below a certain level (The Economist, 2016). Hence, the algorithms' protocols changed based on a host of situational factors that the algorithms themselves integrated into their own protocols in near-real time. Likewise, contemporary AI technologies are capable of learning, adjusting their behaviours, and making autonomous complex decisions in near-real time. Such technologies include machine learning (ML) algorithms (and their deep learning and reinforcement learning subclasses), neural networks, Natural Language Processing, robots, various automation technologies (including robotic process automation), and rule-based expert systems (cf. Benbya et al., 2021, p. 283). For example, ML algorithms are endowed with augmentation capabilities whereby machines learn from humans via training datasets and humans learn from the machines themselves (Ibid: 285). Strands of ML research now draw on a complex-systems perspective to study how ML algorithms and agents (e.g., individuals, organisations, IS, etc.) interact in complex and unpredictable ways, thus triggering unexpected or unanticipated outcomes in a bi-directional fashion (Padmanabhan et al., 2022). We submit that in these contexts, the synchronic mechanisms that account for bi-directional causality are concealed. Accordingly, analysts must conjecture them in a retroductive fashion (Bunge, 2004). Therefore, retroduction offers IS researchers the possibility to reinvent the theory-building process by developing multiple conjectures or hunches that "can uncover latent relationships that may *prima facie* appear to be unrelated" (Tremblay et al., 2021, p. 457).[9]

As well as ML algorithms, automated trading systems, and autonomous vehicles, many other autonomous technologies can trigger real-time or near-real time outcomes without continuous human intervention (Berente et al., 2021; Markus & Rowe, 2018). Synchronic effects among decentralised autonomous organisations, smart contracts, and cryptocurrency will further extend the scope and significance of automated interactions. Accordingly, this paper makes a theoretical contribution to the nascent IS literature on causal mechanisms (e.g., Avgerou, 2013; Markus & Rowe, 2018; Mingers, 2014; Mingers & Standing, 2017). Autonomous technologies are bound to generate real-time synchronic effects where space and time tend to converge. We submit that these synchronic effects can be captured more insightfully with a retroductive mode of inference which is based on counterfactual thinking considering that counterfactual thinking enables IS scholars to grasp the "systemic connections" triggered by small differences in the operation of digital technologies.

Very recently, Critical Realist scholars have envisaged potential methodological limitations and challenges when examining mechanisms (Gebre-Mariam & Bygstad, 2019). "First, the identification and focus on one mechanism at the exclusion of another may produce research that partially explains a phenomenon. Secondly, the lack of clear criteria in Critical Realism around selection among candidate mechanisms leaves much choice to researchers which can introduce potential arbitrariness or partiality" (Ibid: 20). We submit that, by leveraging the principle of theoretical multiplicity when using the QCA counterfactual approach (Park et al., 2020), Critical Realist scholars can draw on multiple theories to explain which configurations of causal conditions can "trigger" or "generate" the outcome of interest. Far from cherry-picking existing theories, Critical Realist researchers should draw on complementary or even competing theories to engage in rigorous theoretical thinking about which counterfactuals are neither questionable nor incoherent with their assumptions (Schneider & Wagemann, 2012). This, in turn, will give Critical Realist researchers clear criteria for selecting between and among "easy" and "difficult" counterfactuals depending on whether such hypothetical configurations are plausible and, therefore, compatible with their theories and assumptions. In short, plausibility becomes a substitute for validity considering that only plausible counterfactuals should be grafted into causal recipes. Indeed, IS scholars should aim for counterfactual cases, "in which the hypothetical antecedent and consequent are close together in time and are separated by a small number of causal steps" (Fearon, 1996, p. 66). The smaller the number of causal steps between the antecedent and the consequent, the more plausible the counterfactual(s) will be.

Furthermore, the retroduction logic calls for multiple robustness tests that "must identify an empirical range within which the same substantive interpretation is plausible (analytical robustness) rather than identify a threshold below which a causal claim is no longer considered valid" (Rutten, 2022, p. 1221). Accordingly, IS scholars are invited to replicate their findings across several frequency and consistency (sufficiency) thresholds ranging from the most lenient to the most stringent thresholds. For example, they should eyeball their truth tables to see if there is a clear gap in consistency levels across truth table rows so as to run their analysis with at least two different consistency thresholds and see "if parameters of fit (i.e., the consistency and coverage scores for the individual paths and the overall solution) dramatically change" (Schneider & Wagemann, 2012, p. 292). While re-analysing the data using the lower and upper thresholds in the gaps should entail a replication of the original findings, it is possible that the new findings will not match the original findings because "QCA results are sensitive to decisions made by the researcher about issues such as the calibration strategy, the selection of cases, and the choice of consistency thresholds among others" (Ibid: 294). In these situations, "the difference in findings probably lies in the way structures and mechanisms are postulated in the theory" (Tsang & Kwan, 1999, p. 770). Accordingly, IS scholars are encouraged to pursue both literal and theoretical replications aimed at obtaining similar results (i.e., literal replications), as well as contrasting results, but for theoretically plausible reasons (i.e., theoretical replications) (cf. Yin, 2014, p. 57). The aforementioned large-N QCA study by Park et al. (2017) is a case in point. Using the proportional reduction in inconsistency (PRI) as a more rigorous parameter to interpret set-theoretic relations of consistency, Park et al. (2017) could have used a more lenient PRI Consistency threshold of 0.65 and a more stringent PRI Consistency threshold of 0.75 to replicate their findings either literally or theoretically. Ultimately, we urge large-N QCA scholars to go back to their data, thus "mirroring the going back to the cases of small-N QCA" scholars (cf. Rutten, 2022, p. 1238) to confirm the analytical robustness of their findings.[10]

Indeed, it is our contention that very few large-N QCA scholars have returned to their data. By failing to return to their data, QCA scholars have implicitly advocated an overly empiricist approach where causal claims are grounded in decontextualized thresholds. For example, Park et al. (2017, p. 684) have recently complained that "we currently lack a widely agreed-on cutoff value for PRI" when, in fact, large-N QCA researchers should go back to their data to constantly update or improve the analytical robustness of their findings. Therefore, causal claims informed by "universally-accepted" thresholds (e.g., standardised frequency thresholds, standardised consistency thresholds, etc.) boil down to statements about empirical regularities rather than statements about causal mechanisms, thus mistaking empirical regularities for the underlying mechanisms that generate them (Rutten, 2021).

Admittedly, the counterfactual approach we advocate in this paper is not without limitations because theory-informed conjectures could be biased by the researchers' theoretical knowledge as they build on the domain knowledge of the researchers themselves. "Consequently, the set of intermediate solutions can vary with the person performing the analysis" (Liu et al., 2017, p. 71). Furthermore, the plausibility of directional expectations in general and conjunctural directional expectations in particular is no easy feat, especially in the domain of contemporary IS phenomena that lack a solid and cumulative body of knowledge. Nevertheless, the counterfactual approach has great potential because it works whether researchers are formulating causal expectations looking at individual conditions or at conjunctions of conditions (cf. Schneider & Wagemann, 2012, pp. 215–217). Moreover, combining QCA with process-tracing methods may provide a new multi-methods approach that may prove very useful for causal analysis in IS research (Wynn & Williams, 2020) because it would interweave synchronic and diachronic causality (Mingers & Standing, 2017).

The discovery of multiple configurations for the outcome of interest may have practical implications too. For example, it may assist managers and policymakers alike in their development of contingency plans as some recipes are bound to be effective in particular contingencies rather than others. This, in turn, may challenge the idea of "best practice" or, analogously, the "herd effects" that occur when managers blindly follow uniform industry practices. A case in point is in the context of big data and analytics considering that managers are likely to "develop different strategies in relation to their big data analytics initiatives" (Mikalef & Krogstie, 2020, p. 278) depending on what environmental and organisational conditions they operate in. Furthermore, big data is associated with greater pools of data and greater associations among them. By building larger pools of data, by creating dependencies between and among them, and by combining and recombining sources, big data is shifting the emphasis from the diachronic to the synchronic view of causality.

6 | CONCLUSION

It is high time IS scholars consider switching from a traditional view of causality to a synchronic view of causality which is more in tune with the near-real time effects generated by the autonomous technologies that surround us. This paper shows that one way to do so is to retroduce synchronic mechanisms by leveraging the QCA counterfactual approach to causation. Using a recently published QCA study as a running example, we show that QCA can be used not only for the purpose of selecting the most plausible mechanisms when there are "a number of potential mechanisms" at play (Tsang, 2014, p. 181). It can also trigger a paradigm shift that requires IS scholars to think "anew" about their indigenous theorising. If information is a difference that makes a difference (McKinney & Yoos, 2010; McKinney & Yoos, 2019), IS scholars will be well served with a more fitting approach that revolves around difference-making rather than production accounts of causality.

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DATA AVAILABILITY STATEMENT

The data that supports the findings of this study is available from the corresponding author upon request.

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ENDNOTES

[1] These hypothetical mechanisms may be conceived of as systems of interacting parts where each part (or causal condition) is an Insufficient but Necessary part of a more complex arrangement (or system) that is Unnecessary but Sufficient (INUS) for achieving the outcome of interest (Mackie, 1965).

[2] It is beyond the scope of this paper to introduce QCA. For a thorough introduction of QCA both as an epistemological approach and a set of techniques, please see Liu et al. (2017). For an overview of Crisp-Set QCA (csQCA) techniques as a way of harnessing longitudinal qualitative data obtained from archived sources, please see Nishant and Ravishankar (2020). Many thanks to the AE and an anonymous reviewer for helping us to illustrate the array of methodological choices available to IS researchers.

[3] Please note that these remarks are not aimed at settling the issue between Positivists (or empiricists) and Critical Realists, let alone argue that the Critical Realists' labels are superior to the Positivists' labels. On the contrary, these remarks are simply aimed at pointing out different ways of labelling the same results.

[4] These empty rows are labelled “remainders” or “potential counterfactuals” because they can be used for counterfactual analysis as described below. Please bear in mind that at this stage (i.e., step one), analysts must also establish the minimum number of cases required for a solution (i.e., a frequency threshold) and the minimum threshold for set-subset relations (i.e., a consistency sufficiency threshold).

[5] Iannacci and Cornford (2018) looked at 10 cases (i.e., Austria, England, Flanders, France, Germany, Greece, Hungary, Italy, Portugal, and Spain), but dropped 3 cases out to compare the most similar cases with the most different outcomes.

[6] Please note that, while software programmes can be used to compute the Simplifying Assumptions (SAs) incorporated in the parsimonious solution or the Easy Counterfactuals (ECs) incorporated in the intermediate solution, the plausibility of directional expectations is not a simple task because it requires a solid body of knowledge that is not always available especially when dealing with contemporary IS phenomena. In these scenarios, retroduction boils down to speculative thought experiments rather than theory-driven thought experiments.

[7] Please see the Appendix for further details. Broadly speaking incoherent simplifying assumptions can either contradict statements about necessary conditions or entail that the same logical remainder is used both in the minimization of the positive outcome configurations and the negative outcome configurations (i.e., the complement of the outcome). Questionable remainders instead are impossible remainders (e.g., the pregnant man) or, more loosely, remainders that are very unlikely to generate the outcome of interest in light of existing theories. Please note that the simplification process has recently generated a controversy among QCA scholars. For example, Thiem (2022) has come up with a more formal definition of INUS causation that advocates the parsimonious solution over the intermediate solution. For a rebuttal of this argument, please see Duşa (2022) who argued that the intermediate solution gets closer to the underlying causal structure, the parsimonious solution being “completely oblivious to all of these so-called untenable assumptions” (Ibid: 559), that is, assumptions on logical remainders that are either questionable or incoherent. Many thanks to an anonymous reviewer for pointing us to this literature.

[8] See Bygstad et al. (2016) for a stepwise framework for identifying the structural components of mechanisms from an affordance perspective.

[9] Many thanks to an anonymous reviewer for suggesting this idea. While we are primarily concerned with synchronic causality in this paper, it is possible that mutual learning effects occur both synchronically and diachronically. In this case, we recommend using a two-step QCA research design aimed at identifying the necessary conditions for the emergence of mutual learning (step 1) and then performing the enhanced standard analysis (step 2) to capture more proximate effects (cf. Schneider, 2019).

[10] Please note that QCA is an evolving methodology. Hence, we refrain from giving clear prescriptions to IS scholars. Nevertheless, when running their robustness tests, IS scholars should be mindful of Ragin's (2008, p. 136) advice that raw consistency scores “between 0.00 and 0.75 indicate the existence of substantial inconsistency.” Broadly speaking, IS scholars should aim for a raw consistency threshold of 0.80 and, in the context of fuzzy-set analysis, a PRI consistency threshold of 0.65 as their most lenient thresholds (cf. Greckhamer, 2016, p. 802; Mattke et al., 2022, p. 560). Furthermore, the choice of consistency thresholds is “heavily dependent on the specific research context” and the analyst's substantive and theoretical knowledge of the research context (cf. Schneider & Wagemann's, 2012, pp. 127–129). When a solid body of theoretical or substantive knowledge is not available, we submit that IS scholars should not simply change empirically derived thresholds such as consistency and frequency thresholds, but they should also make several analytical changes in their theoretical expectations by computing several intermediate solutions and checking whether, and to what extent, such solutions overlap with the solutions obtained by changing the empirically derived thresholds (cf. Oana et al., 2021, pp. 143–158 for general guidelines).

REFERENCES

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and the synthetic control method. *American Journal of Political Science*, *59*(2), 495–510.

Archer, M. S. (1995). *Realist social theory: The morphogenetic approach*. Cambridge University Press.

Avgerou, C. (2013). Social mechanisms for causal explanation in social theory based IS research. *Journal of the Association for Information Systems*, *14*(8), 399–419.

Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). Special issue editorial: Artificial intelligence in organizations: Implications for information systems research. *Journal of the Association for Information Systems*, *22*(2), 281–303.

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly*, *45*(3), 1433–1450.

Bergene, A. (2007). Towards a critical realist comparative methodology: Context-sensitive theoretical comparison. *Journal of Critical Realism*, *6*(1), 5–27.

Bunge, M. (1997). Mechanism and explanation. *Philosophy of the Social Sciences*, *27*(4), 410–465.

Bunge, M. (2004). How does it work? The search for explanatory mechanisms. *Philosophy of the Social Sciences*, *34*(2), 182–210.

Burton-Jones, A., McLean, E. R., & Monod, E. (2015). Theoretical perspectives in IS research: From variance and process to conceptual latitude and conceptual fit. *European Journal of Information Systems*, *24*(6), 664–679.

Bygstad, B. (2010). Generative mechanisms for innovation in information infrastructures. *Information and Organization*, *20*(3–4), 156–168.

Bygstad, B., Munkvold, B. E., & Volkoff, O. (2016). Identifying generative mechanisms through affordances: A framework for critical realist data analysis. *Journal of Information Technology*, *31*(1), 83–96.

Cornelissen, J., Höllerer, M. A., & Seidl, D. (2021). What theory is and can be: Forms of theorizing in organizational scholarship. *Organization Theory*, *2*(3), 1–19. https://doi.org/10.1177/26317877211020328

Danermark, B., Ekstrom, M., & Jakobsen, L. (2002). *Explaining society: An introduction to critical realism in the social sciences*. Routledge.

De Block, D., & Vis, B. (2019). Addressing the challenges related to transforming qualitative into quantitative data in qualitative comparative analysis. *Journal of Mixed Methods Research*, *13*(4), 503–535.

de Guinea, A. O., & Webster, J. (2017). Combining variance and process in information systems research: Hybrid approaches. *Information and Organization*, *27*(3), 144–162.

DeLanda, M. (2006). *A new philosophy of society: Assemblage theory and social complexity*. Continuum.

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research*, *3*(1), 60–95.

Duşa, A. (2022). Critical tension: Sufficiency and parsimony in QCA. *Sociological Methods & Research*, *51*(2), 541–565.

El Sawy, O. A., Malhotra, A., Park, Y., & Pavlou, P. A. (2010). Research commentary—Seeking the configurations of digital ecodynamics: It takes three to tango. *Information Systems Research*, *21*(4), 835–848.

Fearon, J. D. (1996). Causes and counterfactuals in social science: Exploring an analogy between cellar automata and historical processes. In P. E. Tetlock & A. Belkin (Eds.), *Counterfactual thought experiments in world politics: Logical, methodological, and psychological perspectives* (pp. 39–67). Princeton University Press.

Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *Academy of Management Review*, *32*(4), 1180–1198.

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, *54*(2), 393–420.

Gebre-Mariam, M., & Bygstad, B. (2019). Digitalization mechanisms of health management information systems in developing countries. *Information and Organization*, *29*(1), 1–22.

George, A. L., & Bennett, A. (2005). *Case studies and theory development in the social sciences*. MIT Press.

Gerring, J. (2008). The mechanismic worldview: Thinking inside the box. *British Journal of Political Science*, *38*(1), 161–179.

Gerrits, L., & Verweij, S. (2013). Critical realism as a meta-framework for understanding the relationships between complexity and qualitative comparative analysis. *Journal of Critical Realism*, *12*(2), 166–182.

Gerrits, L., & Pagliarin, S. (2020). Social and causal complexity in qualitative comparative analysis (QCA): Strategies to account for emergence. *International Journal of Social Research Methodology*, *1-14*, 501–514. https://doi.org/10.1080/13645579.2020.1799636

Goertz, G., & Mahoney, J. (2012). *A tale of two cultures: Qualitative and quantitative research in the social sciences*. Princeton University Press.

Greckhamer, T. (2016). CEO compensation in relation to worker compensation across countries: The configurational impact of country-level institutions. *Strategic Management Journal*, *37*(4), 793–815.

Greckhamer, T., Misangyi, V. F., & Fiss, P. C. (2013). The two QCAs: From a small-N to a large-N set theoretic approach. In P. C. Fiss, B. Cambré, & A. Marx (Eds.), *Configurational theory and methods in organizational research* (pp. 49–75). Emerald Group Publishing Limited.

Hedström, P., & Swedberg, R. (1998). Social mechanisms: An introductory essay. In *Social mechanisms: An analytical approach to social theory* (pp. 1–31). Cambridge University Press.

Hedström, P., & Ylikoski, P. (2010). Causal mechanisms in the social sciences. *Annual Review of Sociology*, *36*, 49–67.

Henfridsson, O., & Bygstad, B. (2013). The generative mechanisms of digital infrastructure evolution. *MIS Quarterly*, *37*(3), 896–931.

Hernes, G. (1998). Real virtuality. In *Social mechanisms: An analytical approach to social theory* (pp. 74–103). Cambridge University Press.

Hovorka, D. S., Germonprez, M., & Larsen, K. R. (2008). Explanation in information systems. *Information Systems Journal*, *18*(1), 23–43.

Iannacci, F., & Cornford, T. (2018). Unravelling causal and temporal influences underpinning monitoring systems success: A typological approach. *Information Systems Journal*, *28*(2), 384–407.

Illari, P. M., & Williamson, J. (2012). What is a mechanism? Thinking about mechanisms across the sciences. *European Journal for Philosophy of Science*, *2*, 119–135.

Illari, P., & Russo, F. (2014). *Causality: Philosophical theory meets scientific practice*. Oxford University Press.

Kitchin, R., & Dodge, M. (2011). *Code/space: Software and everyday life*. MIT Press.

Lipton, P. (2004). *Inference to the best explanation*. Routledge.

Liu, Y., Mezei, J., Kostakos, V., & Li, H. (2017). Applying configurational analysis to IS behavioural research: A methodological alternative for modelling combinatorial complexities. *Information Systems Journal*, *27*(1), 59–89.

Mackie, J. L. (1965). Causes and conditions. *American Philosophical Quarterly*, *2*(4), 245–264.

Mahoney, J. (2001). Review essay- beyond correlational analysis: Recent innovations in theory and method. *Sociological Forum*, *16*(3), 575–593.

Markus, M. L., & Robey, D. (1988). Information technology and organizational change: Causal structure in theory and research. *Management Science*, *34*(5), 583–598.

Markus, M. L., & Rowe, F. (2018). Is IT changing the world? Conceptions of causality for information systems theorizing. *MIS Quarterly*, *42*(4), 1255–1280.

Mattke, J., Maier, C., Weitzel, T., Gerow, J. E., & Thatcher, J. B. (2022). Qualitative comparative analysis (QCA) in information systems research: Status quo, guidelines, and future directions. *Communications of the association for information systems*, *50*(1), 556–588.

McKinney, E. H., Jr., & Yoos, C. J. (2010). Information about information: A taxonomy of views. *MIS Quarterly*, *34*(2), 329–344.

McKinney, E. H., Jr., & Yoos, C. J. (2019). Information as a difference: Toward a subjective theory of information. *European Journal of Information Systems*, *28*(4), 355–369.

Mikalef, P., & Krogstie, J. (2020). Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. *European Journal of Information Systems*, *29*(3), 260–287.

Mingers, J. (2004). Real-izing information systems: Critical realism as an underpinning philosophy for information systems. *Information and Organization*, *14*(2), 87–103.

Mingers, J. (2014). *Systems thinking, critical realism and philosophy: A confluence of ideas*. Routledge.

Mingers, J., & Standing, C. (2017). Why things happen–developing the critical realist view of causal mechanisms. *Information and Organization*, *27*(3), 171–189.

Mingers, J., Mutch, A., & Willcocks, L. (2013). Critical realism in information systems research. *MIS Quarterly*, *37*(3), 795–802.

Mohr, L. B. (1982). *Explaining organizational behavior*. Jossey-Bass.

Nishant, R., & Ravishankar, M. N. (2020). QCA and the harnessing of unstructured qualitative data. *Information Systems Journal*, *30*(5), 845–865.

Norman, D. (1988). *The design of everyday things*. MIT Press.

Oana, I. E., Schneider, C. Q., & Thomann, E. (2021). *Qualitative comparative analysis using R: A beginner's guide*. Cambridge University Press.

Padmanabhan, B., Sahoo, N., & Burton-Jones, A. (2022). Machine learning in information systems research. *MIS Quarterly*, *46*(1), iii–xix.

Park, Y., El Sawy, O. A., & Fiss, P. C. (2017). The role of business intelligence and communication Technologies in Organizational Agility: A configurational approach. *Journal of the Association for Information Systems*, *18*(9), 648–686.

Park, Y., & Mithas, S. (2020). Organized complexity of digital business strategy: A configurational perspective. *MIS Quarterly*, *44*(1), 85–127.

Park, Y., Fiss, P. C., & El Sawy, O. A. (2020). Theorizing the multiplicity of digital phenomena: The ecology of configurations, causal recipes, and guidelines for applying QCA. *MIS Quarterly*, *44*(4), 1493–1520.

Pawson, R., & Tilley, N. (1997). *Realistic evaluation*. Sage.

Ragin, C. C. (1987). *The comparative method: Moving beyond qualitative and quantitative strategies*. University of California Press.

Ragin, C. C. (1994). *Constructing social research: The unity and diversity of method*. Pine Forge Press.

Ragin, C. C. (2000). *Fuzzy-set social science*. University of Chicago Press.

Ragin, C. C. (2006). Set relations in social research: Evaluating their consistency and coverage. *Political Analysis*, *14*(3), 291–310.

Ragin, C. C. (2008). *Redesigning social enquiry*. The University of Chicago Press.

Ragin, C. C. (2009). Qualitative comparative analysis using fuzzy sets (fsQCA). In *Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques* (pp. 87–121). Sage Publications.

Ragin, C., & Davey, S. (2016). *Fuzzy-set/qualitative comparative analysis 3.0*. Department of Sociology, University of California.

Ragin, C. C., & Sonnett, J. (2005). Between complexity and parsimony: Limited diversity, counterfactual cases, and comparative analysis. In *Vergleichen in der Politikwissenschaft* (pp. 180–197). Springer.

Rohlfing, I., & Schneider, C. Q. (2018). A unifying framework for causal analysis in set-theoretic multimethod research. *Sociological Methods & Research*, *47*(1), 37–63.

Rutten, R. (2019). *Critical Realism and causality: On the assumptions you buy in to when you are making causal claims*. Public Lecture, Tilburg University, Wolf Publishers. Accessed May 14, 2020. http://roelrutten.com/research-roel-rutten-4.pdf

Rutten, R. (2021). Uncertainty, possibility and causal power in QCA. *Sociological Methods and Research*. https://doi.org/10.1177/00491241211031268

Rutten, R. (2022). Applying and assessing large-N QCA: Causality and robustness from a critical realist perspective. *Sociological Methods and Research*, *51*(3), 1211–1243. https://doi.org/10.1177/0049124120914955

Sætre, A. S., & Van de Ven, A. (2021). Generating theory by abduction. *Academy of Management Review*, *46*(4), 684–701.

Schneider, C. Q. (2019). Two-step QCA revisited: The necessity of context conditions. *Quality & Quantity*, *53*(3), 1109–1126.

Schneider, C. Q., & Wagemann, C. (2012). *Set-theoretic methods for the social sciences: A guide to qualitative comparative analysis*. Cambridge University Press.

Seddon, P. B. (1997). A respecification and extension of the DeLone and McLean model of IS success. *Information Systems Research*, *8*(3), 240–253.

Soda, G., & Furnari, S. (2012). Exploring the topology of the plausible: Fs/QCA counterfactual analysis and the plausible fit of unobserved organizational configurations. *Strategic Organization*, *10*(3), 285–296.

Steinmetz, G. (1998). Critical realism and historical sociology. A review article. *Comparative studies in society and history*, *40*(1), 170–186.

The Economist (2016). Why Sterling suffered a "flash crash": flash and the firestorm. London, *421*, 9011:68. Accessed October 15, 2016.

The Guardian (2016). What caused the Pound flash crash? Accessed May 14, 2020. https://www.theguardian.com/business/2016/oct/07/what-caused-pound-flash-crash-brexit-fallen-sterling

Thiem, A. (2022). Beyond the facts: Limited empirical diversity and causal inference in qualitative comparative analysis. *Sociological Methods & Research*, *51*(2), 527–540.

Tóth, Z., Henneberg, S. C., & Naudé, P. (2017). Addressing the 'Qualitative'in fuzzy set qualitative comparative analysis: The generic membership evaluation template. *Industrial Marketing Management*, *63*, 192–204.

Tremblay, M. C., Kohli, R., & Forsgren, N. (2021). Theories in flux: Reimagining theory building in the age of machine learning. *MIS Quarterly*, *45*(1), 455–459.

Tsang, E. W. (2014). Case studies and generalization in information systems research: A critical realist perspective. *The Journal of Strategic Information Systems*, *23*(2), 174–186.

Tsang, E. W., & Kwan, K. M. (1999). Replication and theory development in organizational science: A critical realist perspective. *Academy of Management Review*, *24*(4), 759–780.

Volkoff, O., & Strong, D. M. (2013). Critical realism and affordances: Theorizing IT-associated organizational change processes. *MIS Quarterly*, *37*(3), 819–834.

Weick, K. E. (1989). Theory construction as disciplined imagination. *Academy of Management Review*, *14*(4), 516–531.

Wynn, D. E., Jr., & Williams, C. K. (2012). Principles for conducting critical realist case study research in information systems. *MIS Quarterly*, *36*(3), 787–810.

Wynn, D. E., Jr., & Williams, C. K. (2020). Recent advances and opportunities for improving critical realism-based case study research in IS. *Journal of the Association for Information Systems*, *21*(1), 50–89.

Yin, R. K. (2014). *Case study research: Design and methods*. Sage Publications.

Zachariadis, M., Scott, S., & Barrett, M. (2013). Methodological implications of critical realism for mixed-methods research. *MIS Quarterly*, *37*(3), 855–879.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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