The analysis of temporally ordered configurations: challenges and solutions

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Introduction

In organizational research there is an increasing interest in the study of configurations, i.e., of “multidimensional constellations of conceptually distinct characteristics that occur together” (Meyer, Tsui and Hinings, 1993: 1175). Frequently, the object of study is a process, i.e., a complex of activities that unfolds over time (e.g., an innovation project, a reorganisation, an implementation process). The characteristics that form the configuration are “conditions” (e.g., conditions *A*, *B*, and *C*) that are present (A, B, C) or absent (a, b, c). The notation ABC, thus, represents the observation that the three conditions *A*, *B*, and *C* are present in a process that is studied. Temporally ordered configurations can be defined as those configurations in which conditions occur in a specific temporal order (e.g., C→A→B, meaning that, in one case, C appears first, A next, and finally B). In this chapter we use the term “(temporal) sequence” for such a temporally ordered configuration. Note that the term “(temporal) order” is used here empirically as a synonym of the word “(temporal or chronological) pattern” and is not meant normatively (as opposed to “disorder”). Specific temporal sequences might generate or allow outcomes that are not generated or allowed by the same configuration of conditions if they appear in another temporal order (e.g., A→B→C or B→A→C). The terms “generating” and “allowing” (an outcome), which are used here in order to avoid the term “cause”, will be discussed below in the section on necessary conditions.

In many fields of social research the temporal order of events (i.e., the fact that these events occur in a specific temporal sequence) is, implicitly or explicitly, considered important for relevant outcomes. Many theories are inherently temporal in the sense that the arrows in chains of variables in conceptual models are interpreted as entailing a temporal lag or duration. Usually, the model itself only represents a-temporal associations between values of the variables in a chain of concepts, but the text that explains the theory represented by the model often entails episodes in which a high value of a variable is processually induced by a preceding high (or low) value of another variable. As has been noted in a large body of literature since the 1980s, the temporal nature of theories that are empirically assessed is not taken into account by the traditional methods of statistical “variance analysis” (Mohr, 1982; Markus and Robey, 1988; Langley, 1999; Pettigrew, 1999). These temporal features are not tested with such methods and, hence, the empirical status of temporal statements is that of mere commentary.

We will illustrate the aims, characteristics and limitations of approaches that have been proposed as tools for the analysis of temporal order with an example. This example is an empirical investigation of “gestation activities” of nascent entrepreneurs, i.e., persons involved in the creation of a new firm. The aim of the analysis is to identify temporal sequences of gestation activities (e.g., C→A→B) that generate or allow a successful outcome of the gestation process, while an occurrence of the same activities in another temporal order (e.g., A→B→C or B→A→C) will not generate or allow that outcome. The various analytic approaches will be evaluated in terms of their ability to achieve this aim.

A distinction can be made between different types of temporal sequence (Abbott 1995). Our data set represents only one such type, the non-recurrent sequence of events, i.e. a temporal sequence of which the (analytical) length cannot be longer than the total number of observed events and in which these events can occur only once. First we discuss Event Structure Analysis (ESA; Heise, 1989) and Optimal Matching (OM; Abbott, 1990 and 1995) and conclude that these approaches cannot provide the kind of analysis that we are aiming at in this chapter. Then we discuss Temporal Qualitative Comparative Analysis (TQCA; Caren and Panofsky, 2005; Ragin and Strand, 2008), an approach that is developed specifically for the analytic problem discussed here. As yet, TQCA has not been applied in empirical studies of temporal sequences because of technical limitations. We then present an alternative approach, Temporal Necessary Condition Analysis (TNCA; based on Dul et al., 2010).

We will now first present the data set that we have chosen for this illustration and discuss its characteristics.

Data: gestation activities

The data set for our analysis is taken from the second Panel Study of Entrepreneurial Dynamics (PSED II; Reynolds and Curtin, 2008). The data obtained includes data on the nature of persons who are actively involved as nascent entrepreneurs, on the activities that they undertake during the start-up process, and on the characteristics of start-up efforts that become new firms. Our data set consists of the data regarding all ambitious high-tech start-ups (N=15) in the PSED II data set. The data set is presented in Table 1. Each row corresponds to a nascent entrepreneur. The first column is the identification number. The next five columns refer to five different gestation activities: (1)

B	Start of research into the Business opportunity (including writing a business plan)
D	Start of product or service Development
F	First availability of Financial support for the gestation process
E	First purchase of Equipment
H	Hiring of a first employee

ID	***B***	***D***	***F***	***E***	***H***	***START-UP***	***QUIT***
1	19	25	--	--	--	--	59
2	19	--	25	25	--	--	33
3	18	18	18	32	--	--	--
4	22	23	23	22	--	--	--
5	15	17	18	17	--	20	--
6	30	32	24	31	--	--	--
7	25	25	25	26	--	29	--
8	29	--	20	20	--	--	32
9	22	--	--	--	--	--	36
10	22	20	22	25	25	25	--
11	19	--	--	--	--	--	41
12	22	23	20	22	22	25	--
13	--	29	29	--	--	--	46
14	27	27	27	--	--	40	--
15	29	29	--	--	--	--	--

Table 1. Data set for the analysis in this chapter

The five gestational activities in this analysis represent events (i.e., start of gestation activities) rather than states (i.e., doing gestation activities for a period of time). The numbers in the cells of Table 1 represent the month number in a series from 1= August 2003 to 59 = July 2008. The last two columns show the outcome. Five gestation processes in this data set have actually resulted in a started firm (Start-up). Six nascent entrepreneurs have quitted the gestation process without having started a firm (Quit). For the four remaining nascent entrepreneurs gestation was still ongoing at the time of the fifth wave of data collection. It is not known whether the nascent entrepreneurs that have not yet completed or quitted the start-up process will eventually succeed in starting a new firm and in continuing it (the data are *right censored*).

We have chosen this data set initially because we are interested in the temporal order of successful gestation. Later, in the process of analysis, we discovered that this data set has two characteristics that make it “difficult” for analysis and hence are particularly useful for an evaluation of different analytic approaches. One of the difficulties is the large number of missing events. Our data show that a firm can start after only a limited number of gestational activities (three out of five in this data set). An approach to the analysis of the temporal order of the events in this data set must be able to deal with this characteristic of the data set. The other characteristic that presents a challenge to the analysis is the quite frequent co-occurrence (i.e., in the same month) of events. Obviously this is not an indication that gestational events occur at exactly the same time, but rather of the fact that relevant temporal order, if any, in this data set means “the temporal order of events that are more distant from each other than four weeks”. One could say that these data are imprecise because they do not specify the week or the exact calendar date of each event. Probably it is more accurate to state that the aim of the designers of PSED II has not been to develop (or to allow that users of the data develop) a process theory in terms of days or weeks but (only) in terms of longer periods of time. The fact that the temporal order of events within a (calendar) month is unknown in this data set implies that we aim at developing a process theory in which the temporal order within a time span of a month is not taken into account. This has an important practical implication for the analysis, namely that we must allow for the fact that co-occurrence of events in one month, such as D and E in case 5, can be consistent with both a theory or hypothesis that states that the one must precede the other (“D must precede E”) *and* with a theory that states that the reverse temporal order should occur (“E must precede D”).

Table 2 presents the data from Table 1 in the form of temporal sequences. Obviously, these sequences only include those events that actually occurred. The occurrence of two or more events in the same month is indicated by slashes between events. Arrows represent the flow of time, i.e. one or more months separate the occurrence of the respective events. Outcome is coded as 1 (= Start-up), 0 (= Quit), and – (= Ongoing).

ID	***SEQUENCE***	***OUTCOME***
1	B → D	0
2	B → F/E	0
3	B/D/F → E	–
4	B/E → D/F	–
5	B → D/E → F	1
6	F → B → E → D	–
7	B/D/F → E	1
8	F/E → B	0
9	B	0
10	D → B/F → E/H	1
11	B	0
12	F → B/E/H → D	1
13	D/F	0
14	B/D/F	1
15	B/D	–

Table 2. Temporal sequences

The aim of the analysis is to discover temporal sequences of these five gestational activities that are causally relevant for an outcome. In this analysis, the desired outcome is defined as starting a firm, whereas quitting the gestation process without starting a firm is considered an undesired outcome or failure.(2)

Event Structure Analysis (ESA) and Optimal Matching (OM)

Two types of approaches have been developed for the empirical analysis of temporal order (Krook, 2006: 9-10). One type of techniques focuses on the temporal order of pairs of events, and builds a model of how an organizational path can be constructed from such pairs. The best known example of this type is Event Structure Analysis (ESA, Heise, 1989). ESA builds a pictorial model of pathways which have empirically shown to exist (with an accompanying text). The model looks like a flowchart with parallel routes and iterative loops. An example of such a flowchart representing the pathways of a case of entrepreneurial decision making can be found in Morse (1998: 112).

If ESA is applied to our data set, the entrance to the model will be the decision to start a firm, and there will be two exits: a successful start-up and quit. The model that is built in ESA is a useful starting point for an analysis of temporal sequences. First, it allows the analyst to identify a limited set of pathways (if iterative loops are ignored) that lead to an exit, i.e. of those pathways that “generate” that exit. Second, it allows the analyst to identify those temporal sequences and stations that must be passed in order to reach an exit point, i.e. of temporal sequences that are necessary for an outcome to be generated. Third, these pathways are intrinsically temporal, which is exactly the type of pathway that we want to analyze in this chapter. However, although an ESA model allows this type of analysis, it is not itself an analytic instrument by which temporal sequences **which generate or allow outcomes** are identified.

ESA, thus, is a form of “within-case” analysis that precedes “cross-case” analysis as aimed at in this chapter. A second type of approaches aims at such a “cross-case” analysis by mapping and comparing the structure of whole temporal sequences. Optimal matching (OM) is the best known example of this type of approach. The principle of the optimal matching technique is the insight that, if we have a limited number of events (or states), every temporal sequence of these events or states can be derived from another one by applying a limited set of procedures: insertion, deletion, and substitution. This allows the analyst to calculate the “distance” between two temporal sequences. The simplest way of calculating the distance between two temporal sequences is to count the number of operations that is required for producing the one from the other. More complex approaches assign different weights to different operations. A substitution might, for instance, get a weight of 1.5 or 2 relative to an insertion or deletion. If all temporal sequences in a data set are compared with each other, the resulting distances can be represented in a so-called “distance matrix”. One may then submit the resulting distance matrix to any standard classification technique (e.g., cluster analysis, multidimensional scaling) to derive families of temporal sequences. A "most typical" temporal sequence may then be found by finding the temporal sequence that minimizes some (possibly weighted) function of the distances to all other temporal sequences (Abbott, 1990). A cluster might be represented by a “typical sequence”, i.e., a sequence that has the smallest average distance to all other sequences in the cluster. Finally, the relation between cluster membership and specific outcomes might be statistically assessed. If such a relation is shown to exist, this result can be non-arbitrarily interpreted in a “narrative” way, i.e., in the form of a story in which events occur in a temporal order that makes sense. The narration will closely follow the temporal order of events as represented in this typical sequence.

The result of the optimal matching approach, thus, is a set of “typical sequences” (which do not need to exist empirically) that differ in the likelihood by which they “generate” the desired outcome. If that likelihood equals or approaches 1.0, then we can consider that sequence a (temporally ordered) configuration that generates the outcome. However, observed likelihoods are much lower in practice, for the simple reason that optimal matching is not designed to cluster sequences on the basis of their outcome. Differences in likelihood can be expressed as odds ratios. For instance, in a recent application of OM to data on gestational activities (very similar to our data set), Gordon (2011: 11) concludes: “The marginal effect for sequence similarity is an 11.7% increase in the odds of becoming operational (b = 0.111, z = 3.873, p = 0.000) and 5.8% increase in the odds of remaining “still trying” (b = 0.060, z = 1.951, p = 0.051) as compared to termination." Note that the problem that OM cannot identify sequences that "generate" an outcome cannot be overcome by applying optimal matching in a set of only those cases that have the desired outcome, because this approach ignores the possibility that there are other cases with similar sequences that result in a failure.

An important limitation of this approach is that the applied permutation statistics have problems with ties as well as non-occurring events (Abbott, 1990:383). As many data sets (like our example) contain ties or non-occurring events the method normally cannot be used for assessing which sequences might generate or allow outcomes. This raises the question whether an approach could be developed in which sequences are clustered from the outset in such a way that their association with the outcome is part of the clustering technique. QCA is an obvious candidate technique for achieving this, because the core element of QCA – the truth table – is in essence a method of clustering configurations based on their association with a specific outcome.

Temporal Qualitative Comparative Analysis (TQCA)

We assume that QCA is familiar to the reader. Although QCA was developed initially for the a-temporal analysis of configurations, recently some proposals have been made for how it could be used for the analysis of temporal sequences. De Meur, Rihoux and Yamasaki (2009) list five “solutions” that have been proposed to deal with temporal order in QCA. One of them is to combine QCA with other techniques such as Event Structure Analysis, discussed above. Another one is “returning to cases in a more qualitative manner”, which boils down to narratively adding temporal information to the non-temporal QCA result. Each of the three remaining solutions, though different in detail, integrates the temporal dimension into the definition of the conditions that are analyzed. The only one of these three solutions that is presented and discussed in the literature as a full-fledged method is Temporal Qualitative Comparative Analysis (TQCA) proposed by Caren and Panofsky (2005) and, partially in response to them, by Ragin and Strand (2008).

The procedure that turns QCA into TQCA is the substitution of conditions (such as B, D, F, E, and H in Table 1) by a set of other conditions that specify temporal relations between them. An example of such a new condition is “business research before development” (notated as B→D in the example below) with the codes 1 (when business research occurs before development) and 0 (when development occurs before business research). Note that “B→D” is just a label (or “variable name”) and that code 0 indicates the temporal sequence D→B.

In our data set this would imply the creation of 10 temporal conditions, one for each possible pair of conditions (B→D, B→F, etc.; see the example below). For each case, each of these 10 temporal conditions is coded as either 1 or 0. The usual QCA procedures can then be applied. The advantage of this procedure is that it allows, in principle, to use QCA software for the analysis. However, there are two problems with the application of TQCA that complicate the analysis of temporally ordered conditions, the problem that co-occurrences (“ties”) cannot be coded and the problem that a code cannot be assigned to a pair of which a condition is missing. Both problems have been discussed in the (small) literature on TQCA and they have, as yet, not been solved. We can illustrate both problems with case 14 in our data set. In this case conditions B, D and F are tied, and conditions E and H are missing:

ID	***B***	***D***	***F***	***E***	***H***
14	27	27	27	--	--

Ties are represented by question marks, and pairs with missing events by the symbol “—” in the following representation of the codes required for the application of TQCA:

ID	***B→D***	***B→F***	***B→E***	***B→H***	***D→F***	***D→E***	***D→H***	***F→E***	***F→H***	***E→H***
14	?	?	—	—	?	—	—	—	—	—

Accidentally, the problem of missing events can partly be solved in our data set which is, as mentioned above, right censored, if we assume that events are not missing because of measurement error – they have occurred but have not been recorded – but only because they have not happened yet. Under this assumption, E and H in case 14 will necessarily be preceded by B, D and F. This allows us to code these pairs accordingly:

ID	***B→D***	***B→F***	***B→E***	***B→H***	***D→F***	***D→E***	***D→H***	***F→E***	***F→H***	***E→H***
14	?	?	1	1	?	1	1	1	1	—

However, E→H cannot be coded, and we still have a number of question marks indicating the unresolved issue of co-occurrence.

The fact that TQCA cannot be applied to this data set or to other data sets with ties and missing events is regrettable because the basic ideas of QCA seem to be sound and applicable, in principle, to our data set. Therefore, it is useful to analyze in more depth why exactly QCA cannot handle ties and missing events.

QCA, sufficiency and necessity

In QCA, the researcher seeks to identify the different configurations that are causally relevant for an outcome (Ragin and Strand, 2008: 431). However, this causal relevance can be of two very different types. It can mean (1) that the configuration ***generates*** the outcome (i.e., it is ***sufficient*** for the outcome) or (2) that the configuration ***allows*** the outcome to occur (i.e., it is ***necessary*** for the outcome). Establishing the one or the other type of causal relevance requires analytically distinct tasks (Ragin and Schneider, 2011). QCA aims at providing both of these two distinct types of analysis.

In what respect is the analysis of sufficient configurations different from the analysis of necessary configurations? In their discussion of this difference, Ragin and Schneider (2011) discuss an example of a condition X_1 which in a given data set occurs in cases that are successful as well as in cases that have failed. If it is the aim of the analysis to identify a configuration that is sufficient for success, then

> “the researcher compares cases with and without the outcome [success] and tries to identify what was overlooked. The researcher concludes that X_1 must be combined with X_2 for the outcome to occur because the cases that combine these two conditions consistently exhibit the outcome, while X_1 cases that lack X_2 fail to exhibit the outcome. Thus, this foray into theory building results in a recipe for the outcome that is more elaborate and *less inclusive* than the initial recipe. […..] Observe that in this investigation, the objective is to establish that the causal condition or recipe is a subset of the outcome. […..] The resulting causal argument is made more restrictive […..] moving to a more combinatorial and nuanced conceptualization of causation. […..] Elaborating a causal argument in a combinatorial manner [means] that fewer instances of the outcome [success] are explained. […..] One of perhaps several recipes for the outcome has been clarified and refined.” (Ragin and Schneider 2011: 159-160; emphasis added by us)

This is contrasted with the analytic strategy that must be applied if the aim of the analysis is to identify a configuration that is necessary for success. Here, the key task for the researcher

> "is to see if there is some other condition that is causally equivalent to X_1 which is found in the cases of the outcome [success] that lack X_1. That is, is there a causal condition shared by [these] cases that is *substitutable* for X_1 as a necessary condition? […..] Assume in this example that the researcher […..] concludes that X_1 and X_2 are causally equivalent as necessary conditions with respect to the outcome in question. [This] results in a recipe for the outcome that is *more inclusive* than the initial recipe because more cases display X_1 *or* X_2 than only X_1." (Ragin and Schneider 2011: 161; emphases in the original)

The essential difference between the two analytic strategies is that the search for sufficient configurations requires that conditions are *added* to the configuration (which makes the configuration more specific and implies that not all successful cases are included in the analysis) and that the search for necessary configurations requires that conditions are *substituted* (which makes the configuration more general and implies that all successful cases are included in the analysis). It is strange that Ragin and Schneider use the term "recipe" for both types of result. It makes more sense to use this term only for a sufficient configuration and to use an alternative term (e.g., "list of essential ingredients") for a necessary configuration.

Drawing an analogy with cooking is illuminating. Take the example of baking grandma's apple pie. The recipe for this pie is a list of ingredients and a set of instructions. If one wants to find out what is necessary for baking the pie successfully, one can improvise both with the ingredients and the instructions. Some pies will turn out good (like grandma's own pies) and other pies will be considered failures. Necessary conditions are only those ingredients and actions that occur in all successful pies. If some of these contain no sugar, and other do not contain eggs, then the list of necessary ingredients can be shortened. The remaining list of items is inclusive because it contains the items that are shared by all successful pies.

Inevitably, however, some of the pies that contain all necessary ingredients and have been baked according to each of grandma’s instructions turn out to be failures, although grandma never failed to bake a delicious pie herself. In order to find out why grandma’s recipe (which contains, she says, everything that you need to bake a great pie) failed to produce a good pie in some cases we are forced to search for other conditions (actions, utensils, temporal orders) that are not yet specified in grandma’s instructions, but that need to be added to her recipe in order to guarantee success. In fact, as we know from experience, the list of such additional conditions is infinite (“Dear, obviously you also need to make sure that ….”) and some of them are very difficult to specify (“You must have a feeling for it”). In order to be sufficient, a recipe must be infinitely more specified and, hence, becomes increasingly more exclusive.

Our cooking example can be generalized. We know that it is *always* possible that a goal-oriented action (scoring a goal, passing an exam, winning a war) fails to achieve its goal due to an event or condition that could not have been foreseen and hence could not have been specified before. Every social process can be halted or misdirected at any point (deliberately or unintended) and hence success can never be guaranteed. Therefore, there is no limitation in principle to the number and the type of conditions that must be added to a “sufficient” configuration in order to actually achieve sufficiency. This fact does not fit well with the aim of QCA to generate the most parsimonious explanation that is possible. The more elaborate, exclusive, and “nuanced” the result, the less parsimonious it is. Sufficient configurations, as identified by QCA (or, for that matter, by any other method) must always be expanded with the phrase “and everything else that is relevant for the outcome”. Sufficient configurations are always underspecified in this sense.

Let us now return to the question why TQCA has problems with ties and missing events. The key procedure in QCA is Boolean minimization, a procedure that reduces the configurations that generate the outcome to the shortest possible Boolean expression. This Boolean procedure requires an input of a *complete* set of *binary* codes (0, 1). It is difficult to meet this requirement in a data set with ties, missing events, and different temporal sequences of the same conditions (e.g. both B→D and D→B). Key to our way of avoiding the limitations of TQCA (discussed below) is that Boolean minimization is used in QCA only to provide for the shortest possible Boolean expression of different equifinal configurations that are ***sufficient*** for the outcome, i.e. to reduce the inherent exclusivity of sufficient configurations. This minimization is not required for the analysis of ***necessary*** configurations. A necessary configuration always consists of conditions that are necessary themselves. It is a list of “ingredients”, each of which can be discovered separately. In other words, a necessary configuration is not the result of a procedure of elaboration which then requires a procedure of minimization, but is rather the result of combining (or adding) conditions that are already “minimal”.

Because really sufficient configurations do not exist and, hence, recipes always need to be made complete by adding the phrase “and everything else that is relevant for the outcome”, it is also more realistic from a practical perspective to try to identify only **necessary** conditions and pathways, i.e., conditions that must be present to allow a desired outcome to emerge. Knowledge about such necessary conditions is of practical value because it allows practitioners to develop policies that **avoid a guaranteed failure**.

The concept of a necessary condition, and by implication of a necessary configuration, is undervalued in research because it is much more difficult to connect this concept (than the concept of a sufficient condition) to the dominant “variance” analytic procedures and their implicit concept of causality. In this common way of thinking a “cause” is seen as a thing, a mechanism or an event that (almost literally) produces the effect. The aim to identify configurations that “generate” an outcome is attractive because it suggests that research findings could be used for the formulation of a recipe for success (“golden bullet”).

Necessary Condition Analysis (NCA and TNCA)

A necessary configuration (e.g., configuration ABC) consists of conditions (A, B, and C) that are themselves necessary. In other words, necessary conditions are cumulative. Hence, necessary configurations can be discovered (or “built”) by first identifying its building blocks, the individual necessary conditions. Conditions that are necessary for an outcome can be found by identifying conditions that are shared by all cases with that outcome (see Dul et al., 2010, for a justification of this analytic strategy).

“Building” a necessary configuration from a data set (only) requires that cases are compared for the occurrence (absence / presence) of single conditions. Such a comparison is rather simple and does not require any technical procedures, of a Boolean or other nature. In a data set as ours, “manual” analysis relying on visual inspection will do the job. When a (smaller or larger) number of necessary conditions have been identified in such a manual analysis, a necessary configuration can be built simply by (cumulatively) bringing the separate necessary conditions together in one configuration. We will apply this manual approach to our data set.

A necessary temporal sequence (e.g., configuration A → B → C) consists of individual sequences (A→ B, and B → C) that are themselves necessary. Hence, in order to find a necessary temporal sequence, we must identify sequences that are shared between all successful cases. Similar to QCA, the first step is building a “truth table” (Ragin, 1987). Table 3 is the truth table derived from Table 2 above.

ROW	***OUTCOME=1 (START-UP)***	***FREQUENCY***
1	B → D/E → F	1
2	B/D/F → E	1
3	D → B/F → E/H	1
4	F → B/E/H → D	1
5	B/D/F	1
	OUTCOME=0 (QUIT)	
6	B	2
7	B → D	1
8	B → F/E	1
9	F/E → B	1
10	D/F	1

Table 3. Truth table for TNCA

The second step is identifying individual sequences and coding these in such a way that they can be compared between the (successful) cases. We take here row 1 and row 2 of Table 3 as an example of how this could be done:

1	B → D/E → F
2	B/D/F → E

We need to identify a temporal order for six pairs of events (B-D, B-E, B-F, D-E, D-F and E-F) and to present them in such a way that visual inspection is facilitated:

1	B → D	B → E	B → F	D/E	D → F	E → F
2	B/D	B → E	B/F	D → E	D/F	F → E

As discussed above, co-occurrence of events in one month (as of B and D in row 2) can be consistent with a hypothesis that states that the one must precede the other (B → D) *as well as* with one that states that the reverse temporal order should occur (D → B).

The configurations in rows 1 and 2 share with each other membership of the category "not in contradiction to B → D", whereas they do not share membership of the category "not in contradiction to D → B". The configuration in row 1 is not a member of the latter category, and the configuration in row 2 is a member of it. If we use the notation "B→D" not as indicating the actual occurrence of a temporal sequence in which B precedes D in a case but rather as indicating "not in contradiction to B preceding D", we can recode the two rows as follows:

1	B → D	B → E	B → F	D → E E → D	D → F	E → F
2	B → D D → B	B → E	B → F F → B	D → E	D → F F → D	F → E

Shared between these two rows are the following sequences: B → D, B → E, B → F, D → E, and D → F. If this would be the result of the analysis of all five successful cases (which it obviously is not), then this result would indicate that it is necessary for a start-up that the temporal order of the gestation activities does not contradict that B precedes D *and* does not contradict that D precedes both E and F. This formulation ("does not contradict") allows treating the co-occurrence of events in the same month as consistent with the necessary sequence. Another, more convenient way of stating the same result is that it is necessary for a start-up that E and F do not precede D *and* that D does not precede B.

Before this analysis can be conducted in the complete set of five configurations in Table 3 we must also find a solution for the coding of sequences between pairs of conditions of which one is absent in the data set, as is the case with H in rows 1 and 2. In our discussion of TQCA we have shown that in our data set this problem can partly be solved if we assume that events are not missing because of measurement error – they have occurred but have not been recorded – but only because they have not happened yet. Under this assumption, in rows 1 and 2, we can be certain that H will always be preceded by the other four conditions.

However, we do not have such a solution for the sequence of E and H in row 5. We need a general solution for missing events, independent of this specific data set. The solution that we propose is to treat missing events in the same way as ties, i.e., by coding them as “not in contradiction to” the temporal sequences that could have occurred if the events had happened. This solution implies that we would assign both code E → H and H → E to row 5.

We can now code all five configurations that result in a start-up (rows 1-5 in Table 3). We only look at rows 1-5 because we are interested in identifying those temporal configurations that are necessary for success, i.e. those factors of which the absence guarantees failure. The result is presented in Table 4.

1	B → D	B → F	**B → E**	**B → H**	D → F	D → E E → D	D → H	E → F	**F → H**	**E → H**
2	B → D D → B	B → F F → B	**B → E**	**B → H**	D → F F → D	D → E	D → H	F → E	**F → H**	**E → H**
3	D → B	B → F F → B	**B → E**	**B → H**	D → F	D → E	D → H	F → E	**F → H** H → F	**E → H** H → E
4	B → D	F → B	**B → E** E → B	**B → H** H → B	F → D	E → D	H → D	F → E	**F → H**	**E → H** H → E
5	B → D D → B	B → F F → B	**B → E**	**B → H**	D → F F → D	D → E	D → H	F → E	**F → H**	**E → H** H → E
SHARED	—	—	**B → E**	**B → H**	—	—	—	—	**F → H**	**E → H**

Table 4. Necessary condition analysis

Four sequences are shared between these five configurations: B→E, B→H, F→H and E→H. Three of these sequences can be combined into a chain: B→E→H. Note that the arrows do not only indicate a temporal order (i.e., a difference in time of occurrence of at least a month) but also includes simultaneousness (as in row 4 of Table 3). Note also that this result does not imply that the sequence must always be present, but only that if two events (e.g., E and H) are present in a case, their temporal sequence must not violate the sequence in the result (e.g., H→E should not occur). Hence, these findings could best be expressed as statements about what should *not* occur in order to allow a desired outcome: H (if present) never before E or F, *and* E (if present) never before B.

If these statements really express temporal conditions that are necessary for the desired outcome, then a violation of any of them should only occur in cases that have failed to achieve the desired outcome. Moreover, a necessary condition statement is only interesting in theoretical and practical terms (i.e., it is not trivial) if violations actually occur. For instance, if every nascent entrepreneur (i.e., entrepreneurs that eventually succeed as well as those that eventually fail) would start thinking about the hiring of employees only after (or at the same time as) equipment has been installed, this would be an interesting finding about gestation as a process (irrespective of its outcome), but it would not be informative about how to proceed in order to be successful. Only if violations of the identified necessary sequences occur in practice (and if they are indeed always associated with failure), then it is practically relevant to formulate an advice to avoid them. Hence it is useful to assess whether such violations occur in the current data set.

Inspection of row 6-10 of Table 3 (“failures”) shows that H does not occur in cases of quitting without having started a firm. This suggests that H, if occurring at all, is strongly linked to a successful completion of the gestation process and hence will always occur late in the gestation process. Quitting, thus, seems to have the logical implication that the stage of hiring will not be reached. It might still be the case that early hiring (i.e., behaving in contradiction to the sequences that we have found) actually is a guarantee for failure, but there is not a case of early hiring in our data set and, hence, we do not know whether late hiring is a characteristic of all gestation processes (including those that result in success) or is really necessary for success. We could test the hypothesis “Early hiring guarantees failure” in another data set to sort this out.

Regarding the remaining result (B→E), there is one case, which is represented by row 9 in Table 3, i.e. in a configuration that is associated with quitting the gestation without starting a firm, in which this condition is violated. The fact that a violation of temporal sequence B→E exists in our data set, and that this violation is associated with failure is consistent with the hypothesis that “equipment (if present) never before business research” is a non-trivial necessary condition for a successful outcome of gestation. Obviously, this finding should be formulated as a hypothesis to be tested in other data sets.

TNCA, thus, has discovered at least one non-trivial necessary sequence for successful gestation, though negatively formulated: equipment never before business research. Arguably this is a relevant finding, both in theoretical and practical terms, because it suggests that, for a successful gestation of ambitious high-tech start-ups, business research cannot be delayed until after equipment or, in other words, that it is necessary not to install any equipment before business research has begun (although these activities might be started in the same month). This is consistent with the intuitively plausible idea that business research needs to precede decisions about what equipment is needed.

Are there also temporal sequences that are “necessary” for quitting the gestation process without having started a firm? Because rows 6-10 of the truth table contain a much smaller number of events, there is not much sequential information available in these rows. Only one necessary sequence for quitting can be identified: “development (if present) never before business research”. If this really is a necessary condition for quitting, then “development before business research” should be a sufficient condition for successfully completing the gestation process with a start-up. The sequence “development before business research” (D→B) is present in row 3 in the truth table (Table 3), which indeed is associated with a successful start-up. It is, however, not immediately clear how this result must be interpreted. It might refer to cases of ambitious high-tech start-ups in which there is, from the outset, so much confidence in the profitability of the intended product or service that this is developed first. If this is a correct interpretation of this result, then it is not the temporal order D→B that is sufficient for the successful outcome but rather the initial confidence of the entrepreneur that induced him/her to develop the product or service before conducting any business research.

Conclusion

This chapter discussed methods that could identify temporal sequences of events that generate or allow a successful outcome of a process, while an occurrence of the same events in another sequence will not generate or allow that outcome. Various approaches were evaluated using a small set of data (with time stamp) on the gestation activities of ambitious nascent entrepreneurs in the high-tech sector. The aim of the analysis was to identify temporal sequences of gestation activities (e.g., C→A→B) that generate or allow a successful outcome of the gestation process, while an occurrence of the same activities in another temporal order (e.g., A→B→C or B→A→C) will not generate or allow that outcome. The various analytic approaches were evaluated in terms of their ability to achieve this aim.

A distinction can be made between different types of temporal sequence (Abbott 1995). We discuss the analysis of only one such type, the non-recurrent sequence of events, i.e. a temporal sequence of which the (analytical) length cannot be longer than the total number of observed events and in which these events can occur only once. This type of temporal sequence is a configuration if defined as “multidimensional constellations of conceptually distinct characteristics that occur together” (Meyer, Tsui and Hinings, 1993: 1175), provided that “occur together” is interpreted as meaning “occur in the same case”.

We have identified three approaches that have been proposed as a tool for the identification of temporal sequences of events that generate or allow a successful outcome of a process, (1) Event Structure Analysis (ESA; Heise, 1989), (2) Optimal Matching (OM; Abbott, 1990 and 1995), and (3) Temporal Qualitative Comparative Analysis.

Event Structure Analysis generates a picture (or “model”) of temporal pathways based on a (chronological) narrative. This is very useful as a tool for getting a comprehensive and consolidated overview of all actually occurring pathways in a data set, in particular if events can reoccur. An ESA model is a relatively much less useful tool for representing the set of actually occurring sequences of non-recurrent events. A truth table such as is generated in QCA is at least equally informative. But the main reason why ESA is not the method we are looking for is that its output (the ESA model) still requires the analysis that we are aiming at (as, for that matter, the truth table in QCA, which is the input for the analysis rather than the output).

Both the ESA model and the QCA truth table are a summary of the results of a "within-case" analysis, whereas our aim only can be achieved by means of some form of "cross-case" (or "comparative") analysis. Optimal Matching is an approach to comparative analysis. It produces clusters of sequences that differ in the likelihood by which they generate an outcome. This is a "variance-based" approach for which we want to find an alternative in this chapter. Moreover, an important limitation of this approach is that the applied permutation statistics have problems with ties as well as non-occurring events (Abbott, 1990:383).

Qualitative Comparative Analysis (QCA), the currently common method used in the analysis of configurations, is able to analyse the causal relevance of the absence or presence of an event (condition), but cannot take the temporal sequence of these events into account. Temporal QCA (TQCA; Caren and Panofsky, 2005; Ragin and Strand, 2008) provides for a solution of this problem, but only if all events are present in all cases and only if events never tie. The core of our paper is a solution for this "technical" problem. Our solution, however, is not technical but more fundamental.

We argue that the technical limitations of TQCA only occur in the process of identifying sufficient configurations, which are discovered by adding ever more specifications to an initial configuration (Ragin and Schneider, 2011). By discussing everyday processes such as baking an apple pie, we demonstrated that this process of adding relevant specifications is infinite in principle and, hence, logically untenable and virtually useless in practice. Having concluded that analysis should focus on searching for necessary configurations instead, we demonstrate that such a necessary condition analysis can easily be performed “manually”, (3) i.e. without making use of QCA software (which, as we argue, serves the analysis of sufficient configurations rather than of necessary configurations).

Endnotes

1. Note that the gestational activities are presented in Table 1 in a way (B–D–F–E–H) that already reflects an implicit process theory in which research and development are assumed to take place before finance can be attracted; that seeking finance will precede the purchase of equipment and that employees will be hired for operating the equipment after equipment is purchased; and that then finally the firm can take off, i.e. generate sales and become profitable. The aim of the analysis is to find out to what extent support for this implicit theory can be found in the data.
2. We will use this language of “success” and “failure” throughout this chapter, although it might be argued that quitting the gestation process without starting a firm can be a successful outcome as well, in particular if gestation is seen as a process of finding out whether a firm can be successful (if the firm is started). Quitting for good reasons can hence be seen as a very welcome outcome of gestation.
3. With more events and more cases, this “manual” procedure can be automated easily with, e.g., a macro in a spreadsheet software program.

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