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A CLASSIFICATION MODEL FOR THE STUDY OF SEQUENTIAL PROCESSES AND INDIVIDUAL DIFFERENCES THEREIN

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CLASSI: A classification model for the study of sequential processes and individual differences therein

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Abstract

In psychological research, one often aims at explaining individual differences in S-R profiles, that is, individual differences in the responses (R) with which people react to specific stimuli (S). To this end, researchers often postulate an underlying sequential process, which boils down to the specification of a set of mediating variables (M) and the processes that link these mediating variables to the stimuli and responses under study. Obviously, a crucial task is to chart how the individual differences in the S-R profiles are caused by individual differences in the S-M link and/or by individual differences in the M-R link. In this paper, we propose a novel model, called CLASSI, which was explicitly designed for this task. In particular, the key principle of CLASSI consists of reducing the S, M, and R nodes of a sequential process to a few mutually exclusive types and inducing a S-M and a M-R person typology from the data, with the S-M person types being characterized in terms of *if* S type *then* M type rules and the M-R person types in terms of *if* M type *then* R type rules. As such, the S-M and M-R person types and their associated if-then rules represent the important individual differences in the S-M and M-R links of the sequential process under study. An algorithm to fit the CLASSI model is described and evaluated in a simulation study. An application of CLASSI to data from the behavioral domain of anger and sadness is discussed. Finally, we relate CLASSI to other methods and discuss possible extensions.

1 Introduction

In psychological research, one often aims at explaining individual differences in S-R profiles, that is, individual differences in the responses (R) with which people react to specific stimuli (S). As a first example, in contextualized personality psychology, individual differences in the display of aggressive behavior are studied in relation to the situations or contexts that elicit the aggressive behavior (Mischel & Shoda, 1995, 1998): for instance, when two persons experience a serious conflict with a friend, one person may become very aggressive, whereas the other person may try to reconcile; in this example, the situations constitute the stimuli and the behaviors the responses. As another example, one may consider psychiatric diagnosis research in which interclinician differences in the diagnosed syndromes of patients are studied (Van Mechelen & De Boeck, 1989); in this example, the specific patients and their diagnosed syndromes are the stimuli and responses, respectively.

To explain such individual differences in S-R profiles, researchers often postulate an underlying sequential process. In most cases, this boils down to the specification of a set of mediating variables (M) and the mechanisms that link these mediating variables to the stimuli and responses under study. For example, in contextualized personality psychology, it is assumed that the occurrence of aggressive behavior in specific situations is mediated by cognitions and affects through the following sequential process (Mischel & Shoda, 1995, 1998), which is graphically represented in Figure 1: (1) When a person finds himself in a specific situation, this situation activates a number of cognitions and affects in the person. (For instance, when two persons experience a serious conflict with a friend, this situation may activate angry feelings in one person and anxiety in the other person.) (2) In turn, the activated cognitions and affects elicit specific behaviors from the person. (For instance, anger may elicit aggressive behavior, whereas anxiety may make a person try to reconcile.) As a second example, in psychiatric diagnosis research, one often postulates that the diagnostic process may be captured by the following sequential process (Ceulemans, Van Mechelen, & Kuppens, 2004; Van Mechelen & De Boeck, 1989), shown in Figure 2: (1) The clinicians first check which

SITUATIONS	$\Rightarrow$	**COGNITIONS** **AFFECTS**	$\Rightarrow$	**BEHAVIORS**
	$\uparrow$		$\uparrow$	
	individual differences?		**individual differences?**	

Figure 1: Graphical representation of the postulated underlying sequential process in contextualized personality psychology

PATIENTS	$\Rightarrow$	**SYMPTOMS**	$\Rightarrow$	**SYNDROMES**
	$\uparrow$		$\uparrow$	
	individual differences?		**individual differences?**	

Figure 2: Graphical representation of the postulated underlying sequential process in psychiatric diagnosis research.

symptoms are displayed by the patient. (2) Subsequently, the clinicians decide whether or not the observed symptoms justify the diagnosis of a specific syndrome. In the latter sequential process, the symptom judgements of the patients constitute the mediating variables.

When postulating such an underlying sequential process, a crucial question is to chart how the individual differences in the S-R profiles are caused by individual differences in the S-M link and/or by individual differences in the M-R link. For example, if the sequential process in Figure 1 is used to explain why Person A displays more aggressive behavior in conflict situations than Person B, it is essential to detect whether conflicts activate other cognitions and affects in Person A than they do in Person B - for instance, conflicts activate angry feelings in Person A and anxiety in Person B - and/or whether some cognitions and affects elicit different behavior from Person A and Person B when activated - for instance, whereas feelings of anger may lead Person A to aggressive behavior, they may make Person B try to reconcile. As to the second example, if one would want to increase the diagnostic agreement between clinicians making use of the sequential process in Figure 2, one has to reveal whether the diagnoses of clinicians differ because the clinicians disagree about which symptoms are displayed by the patient and/or because the clinicians disagree about the diagnoses that are justified by the symptoms judged to be present.

Given a postulated sequential process, charting the way in which individual differences in the S-R profiles are caused by individual differences in the S-M link and/or by individual differences in the M-R link of the process is a complex task, however: Firstly, the three sets of variables that constitute the nodes of the sequential process - stimuli, mediating variables, responses -, may each contain a considerable number of elements. Secondly, there may be individual differences in the links between these nodes, where the structure of these individual differences may itself differ from link to link. In this paper we propose a model, called classification model for the study of sequential processes and individual differences therein (CLASSI), designed for this complex task.

The remainder of this paper is organized as follows: In Section 2, the new CLASSI model is introduced. Section 3 describes the aim of and an algorithm for CLASSI data analysis. In Section 4, the results of a simulation study to evaluate the algorithm's performance are reported. Section 5 illustrates the CLASSI model with an application to data from contextualized personality psychology. In Section 6, we relate CLASSI to other methods and we discuss possible extensions of the CLASSI method.

2 The CLASSI model

2.1 Data

To study a specific sequential process and individual differences therein, researchers will often gather information regarding the presence/absence of the postulated mediating variables and the responses, given a set of stimuli. For example, to study individual differences in the situation - cognition/affect - behavior sequential process in Figure 1, a number of persons may be asked to indicate for a number of situations (1) which cognitions and affects these situations activate and (2) which behaviors they would display. Similarly, to study individual differences in the patient - symptom - syndrome sequential process in Figure 2, a number of clinicians may be asked to

Table 1: Hypothetical data arrays $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$

		$\underline{\mathbf{X}}^M$: cognitions/affects				$\underline{\mathbf{X}}^R$: behaviors			
person	situation	other-blame	anger	self-blame	guilt	shout	curse	slam doors	throw things
1	conflict with friend	0	0	1	1	1	1	0	0
	conflict with partner	0	0	1	1	1	1	0	0
	fail exam	0	0	1	1	1	1	0	0
	hand in weak paper	0	0	1	1	1	1	0	0
2	conflict with friend	0	0	1	1	0	0	1	1
	conflict with partner	0	0	1	1	0	0	1	1
	fail exam	0	0	1	1	0	0	1	1
	hand in weak paper	0	0	1	1	0	0	1	1
3	conflict with friend	1	1	0	0	0	0	1	1
	conflict with partner	1	1	0	0	0	0	1	1
	fail exam	0	0	1	1	1	1	0	0
	hand in weak paper	0	0	1	1	1	1	0	0
4	conflict with friend	1	1	0	0	1	1	0	0
	conflict with partner	1	1	0	0	1	1	0	0
	fail exam	0	0	1	1	0	0	1	1
	hand in weak paper	0	0	1	1	0	0	1	1
5	conflict with friend	1	1	0	0	0	0	1	1
	conflict with partner	1	1	0	0	0	0	1	1
	fail exam	1	1	0	0	0	0	1	1
	hand in weak paper	1	1	0	0	0	0	1	1
6	conflict with friend	1	1	0	0	1	1	0	0
	conflict with partner	1	1	0	0	1	1	0	0
	fail exam	1	1	0	0	1	1	0	0
	hand in weak paper	1	1	0	0	1	1	0	0

indicate for a number of patients (1) which symptoms are displayed by the patient and (2) which syndrome(s) can be diagnosed. In general, such a data gathering results in a binary I stimulus $\times$ J mediating variable $\times$ K person data array $\underline{\mathbf{X}}^M$ and a binary I stimulus $\times$ L response $\times$ K person data array $\underline{\mathbf{X}}^R$ that have the stimulus and person modes in common. In this section, the hypothetical binary 4 situations $\times$ 4 cognitions/affects $\times$ 6 persons data array $\underline{\mathbf{X}}^M$ and 4 situations $\times$ 4 behaviors $\times$ 6 persons data array $\underline{\mathbf{X}}^R$ in Table 1 will be used as a guiding example.

2.2 Model

As stated in the introduction, the study of sequential processes and individual differences therein is complex, because (1) the three sets of variables that constitute the nodes of such processes - stimuli, mediating variables, responses -, may each contain a considerable number of elements, and (2) individual differences may occur in the links between these nodes, where the structure of these individual differences may in turn differ from link to link. To deal with this complexity, the CLASSI model first reduces the stimuli, mediating variables and responses to a few mutually exclusive types. Subsequently, the CLASSI model captures the individual difference structures in the S-M and M-R links of the sequential process by inducing two person typologies from the data, with the types of the first person typology being characterized in terms of *if* stimulus type *then* mediating variable type rules and the types of the second person typology in terms of *if* mediating variable type *then* response type rules.

In the following paragraphs we will consecutively discuss the ingredients of a CLASSI model and the reconstruction of the data arrays $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$:

Ingredients of a CLASSI model. A CLASSI model contains three binary matrices describing the typologies of the stimuli, mediating variables, and responses respectively: an $I \times P$ stimulus typology matrix $\mathbf{S}$, a $J \times Q$ mediating variable typology matrix $\mathbf{M}$, and a $L \times S$ response typology matrix $\mathbf{R}$, where a 1-entry indicates that the corresponding element belongs to the type in question. Note that in order to obtain typologies with mutually exclusive and nonempty types, that is, partitions, the rows and columns of each typology matrix are restricted to sum to 1 and at least 1 respectively. Next to the stimulus, mediating variable, and response typology matrices, a CLASSI model implies two binary person typology matrices $\mathbf{P}^{S-M}$ $(K \times R)$ and $\mathbf{P}^{M-R}$ $(K \times T)$, one for each link of the sequential process. Finally, the CLASSI model represents the *if* stimulus type *then* mediating variable type rules and *if* mediating variable type *then* response type rules that characterize the types of these two person typologies in binary linking arrays $\underline{\mathbf{L}}^{S-M}$ $(P \times Q \times R)$ and $\underline{\mathbf{L}}^{M-R}$ $(Q \times S \times T)$ respectively. The number of stimulus types, mediating variable types, S-M person types, behavior types, and M-R person types (P,Q,R,S,T) hereby denotes the rank of the CLASSI model. For our guiding example, Table 2 shows a (2,2,3,2,2) CLASSI decomposition of $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$ in Table 1. With respect to the typologies, from Table 2, one may for instance derive that 'conflict with friend' and 'conflict with partner' constitute the first situation type ST_1,

Table 2: (2,2,3,2,2) CLASSI decomposition of $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$ in Table 1

situation typology matrix $\mathbf{S}$			cogn./aff. typology matrix $\mathbf{M}$			behavior typology matrix $\mathbf{R}$		
	situation type			cogn./aff. type			behavior type	
situation	ST_1	ST_2	cogn./aff.	MT_1	MT_2	behavior	RT_1	RT_2
conflict with friend	1	0	other-blame	1	0	shout	1	0
conflict with partner	1	0	anger	1	0	curse	1	0
fail exam	0	1	self-blame	0	1	slam doors	0	1
hand in weak paper	0	1	guilt	0	1	throw things	0	1

S-M person typology matrix $\mathbf{P}^{S-M}$				M-R person typology matrix $\mathbf{P}^{M-R}$		
	S-M person type				M-R person type	
person	PT_1^{S-M}	PT_2^{S-M}	PT_3^{S-M}	person	PT_1^{M-R}	PT_2^{M-R}
1	1	0	0	1	1	0
2	1	0	0	2	0	1
3	0	1	0	3	1	0
4	0	1	0	4	0	1
5	0	0	1	5	1	0
6	0	0	1	6	0	1

S-M linking array $\underline{\mathbf{L}}^{S-M}$				M-R linking array $\underline{\mathbf{L}}^{M-R}$			
		cogn./aff. type				behavior type	
S-M person type	situation type	MT_1	MT_2	M-R person type	cogn./aff. type	RT_1	RT_2
PT_1^{S-M}	ST_1	0	1	PT_1^{M-R}	MT_1	0	1
	ST_2	0	1		MT_2	1	0
PT_2^{S-M}	ST_1	1	0	PT_2^{M-R}	MT_1	1	0
	ST_2	0	1		MT_2	0	1
PT_3^{S-M}	ST_1	1	0				
	ST_2	1	0				

whereas 'fail exam' and 'hand in weak paper' form the second situation type ST_2. Note that two persons may belong to the same S-M person type, but to different M-R person types, and vice versa. With respect to the linking rules, it can for instance be read that the first situation type ST_1 activates the second cognition/affect type MT_2 for the first M-R person type PT_1^{M-R}: $l_{121}^{S-M} = 1$.

Reconstruction of $\underline{\mathbf{X}}^M$. Given the typology matrices $\mathbf{S}$, $\mathbf{M}$, $\mathbf{P}^{S-M}$, and the linking array $\underline{\mathbf{L}}^{S-M}$, the reconstructed data array $\hat{\underline{\mathbf{X}}}^M$ can be derived as follows: A stimulus i will activate a mediating variable j in person k (i.e., $\hat{x}_{ijk}^M = 1$) if the stimulus type p to which i belongs activates the mediating variable type q to which j belongs in the S-M person type r to which k belongs. For instance, from the model in Table 2, it can be derived that a conflict with a friend activates the feeling of guilt in Person 2, since the types to which these elements respectively belong (ST_1, MT_2, and PT_1^{S-M}), are linked in the S-M linking array $\underline{\mathbf{L}}^{S-M}$: $l_{121}^{S-M} = 1$. Formally, this rule can be written as:

$$x_{ijk}^{M} \approx \hat{x}_{ijk}^{M} = \sum_{p=1}^{P}\sum_{q=1}^{Q}\sum_{r=1}^{R} s_{ip} m_{jq} p_{kr}^{S-M} l_{pqr}^{S-M}. \tag{1}$$

Note that this rule is the decomposition rule of a three-mode partitioning model (Schepers, Van Mechelen, & Ceulemans, in press), subject to the restriction that $\underline{\mathbf{L}}^{S-M}$ and hence also $\underline{\hat{\mathbf{X}}}^{M}$ is binary.

Reconstruction of $\underline{\mathbf{X}}^{R}$. The reconstructed data array $\underline{\hat{\mathbf{X}}}^{R}$ can be computed as follows: A stimulus i will activate a response l in person k (i.e., $\hat{x}_{ilk}^{R} = 1$) if i activates *at least* one mediating variable type q in k for which holds that q elicits the behavior type s to which l belongs from the M-R person type t to which k belongs. For instance, from the model in Table 2, it can be derived that Person 2 will start slamming doors when he or she experiences a conflict with a friend, because the types to which Person 2 and 'slam doors' belong (RT_2 and PT_2^{M-R}), are linked in $\underline{\mathbf{L}}^{M-R}$ to the second cognition/affect type (MT_2), which is activated by 'conflict with a friend' in Person 2: $l_{222}^{M-R} = 1$. The latter rule can be formalized as:

$$x_{ilk}^{R} \approx \hat{x}_{ilk}^{R} = \bigoplus_{q=1}^{Q}\bigoplus_{s=1}^{S}\bigoplus_{t=1}^{T} h_{ikq} r_{ls} p_{kt}^{M-R} l_{qst}^{M-R}, \tag{2}$$

where $\bigoplus$ denotes the Boolean sum and h_{ikq}, computed as

$$h_{ikq} = \sum_{p=1}^{P}\sum_{r=1}^{R} s_{ip} p_{kr}^{S-M} l_{pqr}^{S-M}, \tag{3}$$

indicates whether situation i activates mediating variable type q in person k.

As such the person types in a CLASSI person typology and their associated if-then rules represent the important individual differences in the corresponding links of the sequential process. For instance, given the data in Table 1 and the associated (2,2,3,2,2) CLASSI model in Table 2, it can be concluded that the individual differences in the S-R profiles are caused by individual differences in the S-M link of the underlying sequential process as well as by individual differences in the M-R link. Furthermore, as the S-M and M-R person typologies make a distinction between three and two person types respectively, the individual differences in the S-M link seem to be more important than the individual differences in the M-R link.

Regarding the uniqueness of a (P,Q,R,S,T) CLASSI decomposition, rule (1) being the decomposition rule of a constrained three-mode partitioning model, it can be proven that the decomposition of $\underline{\hat{\mathbf{X}}}^M$ in the typology matrices $\mathbf{S}$, $\mathbf{M}$, $\mathbf{P}^{S-M}$ and the linking array $\underline{\mathbf{L}}^{S-M}$ is unique (upon a permutation of the types) if $\mathbf{S}$, $\mathbf{M}$, $\mathbf{P}^{S-M}$, and $\underline{\mathbf{L}}^{S-M}$ are of full rank, that is, if (1) $\mathbf{S}$, $\mathbf{M}$, $\mathbf{P}^{S-M}$ contain no empty types and (2) no stimulus (mediating variable, person) slice of $\underline{\mathbf{L}}^{S-M}$ equals another stimulus (mediating variable, person) slice (see, Schepers et al., in press). The decomposition of $\underline{\hat{\mathbf{X}}}^R$ into the typology matrices $\mathbf{R}$, $\mathbf{P}^{M-R}$ and the linking array $\underline{\mathbf{L}}^{M-R}$ is not always unique, however. We propose to address this issue by indicating which entries of the linking array $\underline{\mathbf{L}}^{M-R}$ can be altered without affecting the reconstructed data array $\underline{\hat{\mathbf{X}}}^R$ and by flagging the responses (resp. persons) that can be assigned to different response types in $\mathbf{R}$ (resp. different M-R person types in $\mathbf{P}^{M-R}$) without affecting $\underline{\hat{\mathbf{X}}}^R$. Note that the (2,2,3,2,2) CLASSI decomposition in Table 2 is unique.

2.3 Graphical representation

The CLASSI model can be given a comprehensive graphical representation. As an example, Figure 3 shows a graphical representation of the CLASSI model in Table 2. Figure 3 can be obtained by first displaying the partitions of the situations, cognitions/affects, behaviors, and persons in five stacks of boxes. Subsequently, the *if* situation type *then* cognition/affect type and *if* cognition/affect type *then* behavior type links can be represented by interconnecting the relevant boxes, using different line styles to indicate for which person type the *if*-*then* relation holds. As such, from

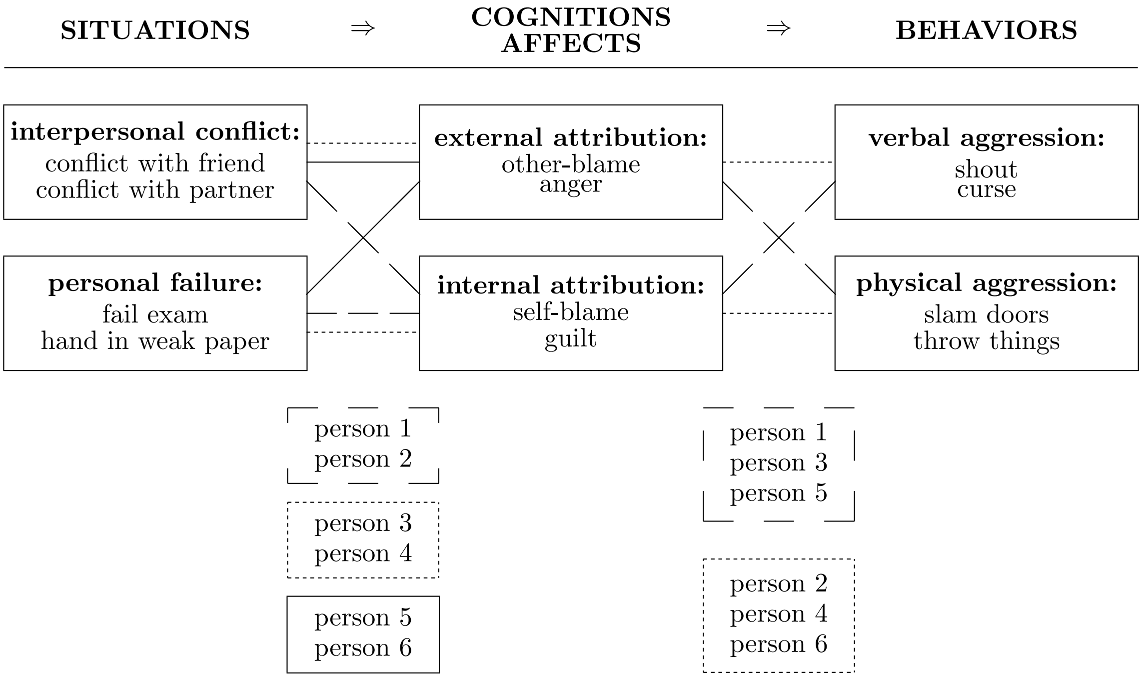

Figure 3: Graphical representation of the (2,2,3,2,2) CLASSI decomposition of $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$ in Table 1

Figure 3, one can for instance derive that the first and second S-M person types only differ with respect to the cognitions/affects that are activated by interpersonal conflict situations: whereas person type PT_1^{S-M} makes an internal attribution, person type PT_2^{S-M} makes an external attribution; both person types make an internal attribution in case of personal failure. The (individual differences in the) M-R links can be read in a similar fashion.

3 Data analysis

3.1 Aim

The aim of a CLASSI analysis in rank (P,Q,R,S,T) of two given binary $I \times J \times K$ and $I \times L \times K$ data arrays $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$ is to look for binary $I \times J \times K$ and $I \times L \times K$ reconstructed data arrays $\underline{\hat{\mathbf{X}}}^M$

and $\underline{\hat{\mathbf{X}}}^R$ that have a minimal value on the least squares (or, equivalently, least absolute deviations) loss function

$$L = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(x_{ijk}^M - \hat{x}_{ijk}^M)^2 + \sum_{i=1}^{I}\sum_{l=1}^{L}\sum_{k=1}^{K}(x_{ilk}^R - \hat{x}_{ilk}^R)^2 \quad (4)$$

and that can be further decomposed into a CLASSI model of the specified rank.

In practice, the true rank of the CLASSI model underlying given data arrays $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$ is almost always unknown, however. Therefore, one will usually fit CLASSI solutions of different ranks to these data arrays. Note, however, that some ranks (P,Q,R,S,T) can be omitted: In particular, it is obvious that a (P,Q,R,S,T) solution with two identical stimulus (resp. mediating variable, person) slices in linking array $\underline{\mathbf{L}}^{S-M}$ is equivalent to the (P-1,Q,R,S,T) (resp. (P,Q-1,R,S,T), (P,Q,R-1,S,T)) solution that is obtained by merging the two corresponding stimulus (resp. mediating variable, person) types. Similarly, a (P,Q,R,S,T) solution with two identical response (resp. person) slices in linking array $\underline{\mathbf{L}}^{M-R}$ is equivalent to the (P,Q,R,S-1,T) (resp. (P,Q,R,S,T-1)) solution that is obtained by merging the two corresponding response (resp. person) types. As a consequence, CLASSI solutions with $P > 2^{QR}$ (resp. $Q > 2^{PR}$, $R > 2^{PQ}$, $S > 2^{QT}$, $T > 2^{QS}$) can be omitted, as, due to the binary nature of $\underline{\mathbf{L}}^{S-M}$ and $\underline{\mathbf{L}}^{M-R}$, these solutions will always contain identical core planes. Having obtained CLASSI solutions of different ranks for given data arrays $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$, a final solution may be selected on the basis of formal rank selection heuristics and the interpretability of the different solutions. As a formal rank selection heuristic, one may consider the numerical convex hull based rank selection heuristic as proposed by Ceulemans and Kiers (2006). This heuristic, which has been shown to work very well for selecting among 3MPCA and multimode partitioning solutions of different complexities (Ceulemans & Kiers, 2006; Schepers, Ceulemans, & Van Mechelen, 2006), selects the solution that is located on the elbow of the lower boundary of the convex hull of a $P + Q + R + S + T$ by L-value plot.

3.2 Algorithm

In this subsection, we propose a simulated annealing (SA, for a general introduction, see Aarts & Lenstra, 1997) algorithm for fitting a (P,Q,R,S,T) CLASSI model to given data arrays $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$. The general principle of an SA algorithm can be described as follows: Starting from an initial solution for the problem at hand and an initial temperature, the algorithm generates a solution chain, which implies a walk through the solution space. In particular, the chain consists of a number of subchains in each of which the following process is repeated until a prespecified subchain stop criterion is met: First, a trial solution is generated on the basis of the current solution, with the first current solution of each subchain being the final solution of the previous subchain. Subsequently, the fit values of the current and trial solutions are compared. If the trial solution fits the data better than the current solution, it is always accepted, implying that the current solution is replaced by the trial solution. However, in order to avoid getting stuck in local minima, also worse fitting trial solutions are sometimes accepted as well. In particular, worse trial solutions are accepted with probability

$$p = exp(\frac{L_{current} - L_{trial}}{T_{current}}), \tag{5}$$

where $L_{current}$ and L_{trial} denote the badness-of-fit values of the current and trial solutions and $T_{current}$ indicates the 'temperature' of the algorithmic process, with $T_{current} > 0$. At the end of each subchain, the temperature is decreased. The generation of subchains stops when a prespecified global chain stop criterion has been satisfied. Finally, an SA algorithm returns the best encountered solution; note that in most cases, this best solution is identical to the final solution of the final subchain.

In the CLASSI algorithm the following specifications and metaparameters have been chosen within the SA framework. First, the initial solution is generated randomly. In particular, initial typology matrices are generated by drawing the type memberships of the elements in a uniform way, subject to the restrictions that each type contains at one least element and that each element belongs to one type only. The entries of the initial linking arrays are independent realizations of a Bernoulli variable with parameter value .5. Second, the initial temperature $T_{initial}$ is estimated by generating one subchain of trial solutions in which all trial solutions are accepted irrespective of their loss function values. Subsequently, all associated $L_{current} - L_{trial}$-values are recorded. Next, the average $L_{current} - L_{trial}$-value is calculated across the worse trial solutions cases, that is, the cases for which $L_{current} < L_{trial}$. Finally, $T_{initial}$ is computed as

$$T_{initial} = \frac{\text{average}(L_{current} - L_{trial})\text{-value of the worse trial solutions}}{ln(.8)}. \tag{6}$$

The rationale behind (6) is that the resulting $T_{initial}$ results in an average acceptance probability of worse trial solutions of .8 (see, e.g., Murillo, Vera, & Heiser, 2005). Third, to generate a trial solution on the basis of a current solution we either randomly assign one stimulus, mediating variable, response or person to another type - subject to the constraint that all types contain at least one element - or we alter the value of one randomly chosen entry of $\underline{\mathbf{L}}^{S-M}$ or $\underline{\mathbf{L}}^{M-R}$ - subject to the constraints that (1) no stimulus (mediating variable, person) slice of $\underline{\mathbf{L}}^{S-M}$ equals another stimulus (mediating variable, person) slice and (2) no response (person) slice of $\underline{\mathbf{L}}^{M-R}$ equals another response (person) slice; the latter constraints are imposed to ensure that the obtained trial solution is of full rank (see subsection 3.1). Note that the generation of trial solutions is performed such that all parameters of the CLASSI model have an equal probability of being altered. Fourth, with respect to the subchain stop criterion, a subchain is considered complete if either $IP + JQ + KR + PQR + LS + KT + QST$ trial solutions have been generated or $.1 * (IP + JQ + KR + PQR + LS + KT + QST)$ trial solutions have been accepted, the latter implying that at $T_{current}$ the solution space has been explored sufficiently (see e.g., Brusco & Stahl, 2000). Fifth, to decrease the temperature $T_{current}$, we multiply it by .95. Sixth, the global chain stop criterion reads that either $T_{current} \leq .000001$ or that no trial solution has been accepted in a subchain.

In view of the uniqueness issues mentioned in section 2.2, the obtained CLASSI solution is post-processed. More in particular, the entries of the linking array $\underline{\mathbf{L}}^{M-R}$ that can be altered without affecting the reconstructed data array $\hat{\underline{\mathbf{X}}}^{R}$ are flagged. Also the responses (resp. persons) that can be assigned to different response types in $\mathbf{R}$ (resp. different M-R person types in $\mathbf{P}^{M-R}$) without affecting $\hat{\underline{\mathbf{X}}}^{R}$ are marked by flagging all types to which the responses and persons belong.

4 Simulation study

In this section, we present the main results of a simulation study performed in order to evaluate the CLASSI algorithm. In particular, we examined how often the CLASSI algorithm returns a local minimum (goodness of fit) and how well it succeeds in recovering the underlying truth (goodness of recovery).

In subsection 4.1, the design of the simulation study is outlined. Next, the results are presented in Subsections 4.2 (goodness of fit) and 4.3 (goodness of recovery).

4.1 Design and procedure

In this simulation study, a distinction is made between three different pairs of an $I \times J \times K$ and an $I \times L \times K$ binary array: true arrays $\underline{\mathbf{T}}^{M}$ and $\underline{\mathbf{T}}^{R}$, which are constructed by the simulation researcher and that can be perfectly represented by a (P,Q,R,S,T) CLASSI model; data arrays $\underline{\mathbf{X}}^{M}$ and $\underline{\mathbf{X}}^{R}$, which are obtained by perturbing $\underline{\mathbf{T}}^{M}$ and $\underline{\mathbf{T}}^{R}$ with error; and reconstructed data arrays $\hat{\underline{\mathbf{X}}}^{M}$ and $\hat{\underline{\mathbf{X}}}^{R}$, which are obtained by analyzing $\underline{\mathbf{X}}^{M}$ and $\underline{\mathbf{X}}^{M}$ with the CLASSI algorithm and, hence, can also be perfectly represented by a (P,Q,R,S,T) CLASSI model.

The design of the CLASSI simulation study consisted of three between-block independent variables:

(a) the *Size*, (I,J,K,L), of $\underline{\mathbf{T}}^{M}$ and $\underline{\mathbf{T}}^{R}$, $\underline{\mathbf{X}}^{M}$ and $\underline{\mathbf{X}}^{R}$, and $\hat{\underline{\mathbf{X}}}^{M}$ and $\hat{\underline{\mathbf{X}}}^{R}$, at 4 levels: (10,10,25,10), (25,25,25,25), (10,10,200,10), (25,25,200,25);

(b) the *True rank*, (P,Q,R,S,T), of the CLASSI model for $\underline{\mathbf{T}}^M$ and $\underline{\mathbf{T}}^R$, at 3 levels: (3,3,3,3,3), (2,3,2,4,4), (3,4,4,2,2);

(c) the *Error level*, ε, which is the proportion of entries x^M_{ijk} (resp. x^R_{ilk}) differing from t^M_{ijk} (resp. t^R_{ilk}), at 3 levels: .00, .10, .20.

For each combination of size, true rank, and error level, 5 replicates were simulated, yielding 4 (size) $\times$ 3 (true rank) $\times$ 3 (error level) $\times$ 5 (replicates) = 180 simulated data sets. In particular, 180 true arrays $\underline{\mathbf{T}}^M$ and $\underline{\mathbf{T}}^R$ were constructed as follows: Typology matrices $\mathbf{S}$, $\mathbf{M}$, $\mathbf{P}^{S-M}$, $\mathbf{R}$, and $\mathbf{P}^{M-R}$ were generated by assigning each of the corresponding elements to a type, where all types had equal probability of being assigned to, subject to the restriction that all types contain at least one element. The entries of the linking arrays $\underline{\mathbf{L}}^{S-M}$ and $\underline{\mathbf{L}}^{M-R}$ were independent realizations of a Bernoulli variable with probability parameter .5, subject to the constraints that (1) no stimulus (mediating variable, person) slice of $\underline{\mathbf{L}}^{S-M}$ equals another stimulus (mediating variable, person) slice and (2) no response (person) slice of $\underline{\mathbf{L}}^{M-R}$ equals another response (person) slice; the latter constraints were imposed to ensure that the true arrays $\underline{\mathbf{T}}^M$ and $\underline{\mathbf{T}}^R$, obtained by combining $\mathbf{S}$, $\mathbf{M}$, $\mathbf{P}^{S-M}$, $\mathbf{R}$, $\mathbf{P}^{M-R}$, $\underline{\mathbf{L}}^{S-M}$, and $\underline{\mathbf{L}}^{M-R}$ by (1) and (2), cannot be perfectly represented by a CLASSI model of a lower rank than the true rank (see subsection 3.1). Subsequently, a data array $\underline{\mathbf{X}}^M$ (resp. $\underline{\mathbf{X}}^R$) was constructed from each true array $\underline{\mathbf{T}}^M$ (resp. $\underline{\mathbf{T}}^R$) by randomly altering the value of a proportion ε of the entries in $\underline{\mathbf{T}}^M$ (resp. $\underline{\mathbf{T}}^R$). Finally, all resulting data arrays $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$ were analyzed 25 times with the CLASSI algorithm, with (P,Q,R,S,T) equal to the corresponding true rank and with each of the 25 runs implying a different random initialization of $S_{current}$; from the 25 resulting CLASSI solutions the solution $\hat{\underline{\mathbf{X}}}^M$ and $\hat{\underline{\mathbf{X}}}^R$ with the lowest loss function value (4) was retained.

4.2 Goodness of fit

In this subsection, we examine the goodness of fit of the obtained CLASSI solutions. More in particular, we are interested in how often the CLASSI algorithm yields a local minimum. In all cases in which the simulated true arrays $\underline{\mathbf{T}}^M$ and $\underline{\mathbf{T}}^R$ are perturbed with nonzero random error to obtain simulated data sets $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$, the global minimum for the CLASSI analysis is unknown, however. In such cases, we can only compare the CLASSI loss function value (4) with the badness-of-data-value BOD - how many entries of the true arrays $\underline{\mathbf{T}}^M$ and $\underline{\mathbf{T}}^R$ were changed of value to obtain the data arrays $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$ -

$$BOD = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(x_{ijk}^M - t_{ijk}^M)^2 + \sum_{i=1}^{I}\sum_{l=1}^{L}\sum_{k=1}^{K}(x_{ilk}^R - t_{ilk}^R)^2. \quad (7)$$

If the loss function value is bigger than the BOD-value, we know for sure that the algorithm yielded a local minimum.

Comparing the loss function values (4) of the 180 CLASSI analyses of the simulated data sets with the corresponding BOD-values, showed that 7 analyses yielded a solution with $L > BOD$; with respect to the other 173 analyses, 166 analyses resulted in a solution with $L = BOD$ and 7 analyses ended in a solution with $L < BOD$. To investigate further the issue of local minima, we examined how many out of the 25 analyses per simulated data set ended in the best obtained solution for that data set: On average, this was the case for 9.56 of the 25 analyses ($SD = 5.74$); an analysis of variance with the number of analyses ending in the best obtained solution as dependent variable revealed no significant main and interaction effects of size, true rank, and error level. From all these results, we conclude that the CLASSI algorithm succeeds well in minimizing the loss function.

4.3 Goodness of recovery

In this subsection, we examine the goodness of recovery of each of the 180 obtained CLASSI solutions. To this end, we computed the proportion of discrepancies between the reconstructed data arrays $\underline{\hat{\mathbf{X}}}^M$ and $\underline{\hat{\mathbf{X}}}^R$ and the corresponding true arrays $\underline{\mathbf{T}}^M$ and $\underline{\mathbf{T}}^R$:

$$BOR = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(\hat{x}_{ijk}^M - t_{ijk}^M)^2 + \sum_{i=1}^{I}\sum_{l=1}^{L}\sum_{k=1}^{K}(\hat{x}_{ilk}^R - t_{ilk}^R)^2}{IJK + ILK}. \tag{8}$$

The results show that 161 analyses perfectly reconstructed the true underlying data set, that is, yielded a solution with a BOR-value of 0 (note that, taking into account the goodness of fit results reported above, at most 166 analyses could result in a BOR-value of 0). The other 19 CLASSI solutions had a mean BOR-value of .0088 (SD = .0145), implying that on average only .88 % of the entries of the true arrays $\underline{\mathbf{T}}^M$ and $\underline{\mathbf{T}}^R$ were reconstructed incorrectly. It can be concluded that the CLASSI algorithm succeeds well in reconstructing the true underlying data set.

5 Illustrative application

In this section, we present a CLASSI analysis of the anger and sadness data gathered by Vansteelandt and Van Mechelen (2006) within the domain of contextualized personality psychology research. This anger and sadness study was based on the Cognitive Affective Personality System (CAPS) theory of Mischel and Shoda (1995, 1998), which conceives personality as a system of cognitions and affects that mediates between situations and behavioral responses. As such, two important questions for CAPS theory are (1) which cognitions and affects mediate between specific situations and behaviors, and (2) are individual differences in situation-behavior profiles accounted for by individual differences in the situation-cognition/affect link and/or by individual differences in the cognition/affect-behavior link. To answer these questions for the behavioral domain of anger and sadness, Vansteelandt and Van Mechelen (2006) asked 258 persons to generate 10 specific negative situations that they had experienced in daily life and that matched a facet-theoretic combination of three abstract situational features: the intensity of the negative event (weakly, strongly), the presence of a familiar other (present, not present), and the cause of the negative event (other, self, no person) (note that the two 'not present-other' combinations are not sensible, which explains why only 10 situations had to be generated rather than the $12 = 2 \times 2 \times 3$ that result from a full crossing of the three facets). Next, the persons indicated on a 3-point scale the degree to which they displayed 11 cognitions and affects and 6 anger and sadness behaviors in these 10 negative situations (0=not, 1=to a limited extent, 2=to a strong extent). The resulting $10 \times 11 \times 258$ and $10 \times 6 \times 258$ data arrays $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$ were dichotomized by recoding 0 to zero and 1 and 2 to one.

CLASSI models in ranks (1,1,1,1,1) through (6,5,5,5,5) were fitted to the dichotomized $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$. Based on the interpretability of the different solutions and the results of the numerical convex hull based rank selection heuristic (Ceulemans & Kiers, 2006; see subsection 3.1), the (6,5,2,3,1) solution was selected, implying 6 situation types, 5 cognition/affect types, 2 S-M person types, 3 behavior types, and 1 M-R person type. Figure 4 shows a graphical representation of this (6,5,2,3,1) solution, with the cognitions and affects being indicated by the keywords presented in Table 3. As the set of possible *if* situation type *then* cognition/affect type rules is rather large (i.e., $6 \times 5 = 30$ possible rules), for the two S-M person types, only the *if* situation *then* cognition/affect type rules that start from the weakly-other situation type are displayed in Figure 4. Figure 5 therefore presents a full overview of the *if* situation type *then* cognition/affect type rules of the two S-M person types. In particular, the upper and lower triangles in the boxes in Figure 5 indicate whether (gray) or not (white) the corresponding *if* situation type *then* cognition/affect type rules hold for the first and second S-M person types PT_1^{S-M} and PT_2^{S-M}, respectively.

The typologies of the situations, cognitions and affects, and behaviors are almost identical to the INDCLAS typologies reported by Vansteelandt and Van Mechelen (2006); hence, we interpreted

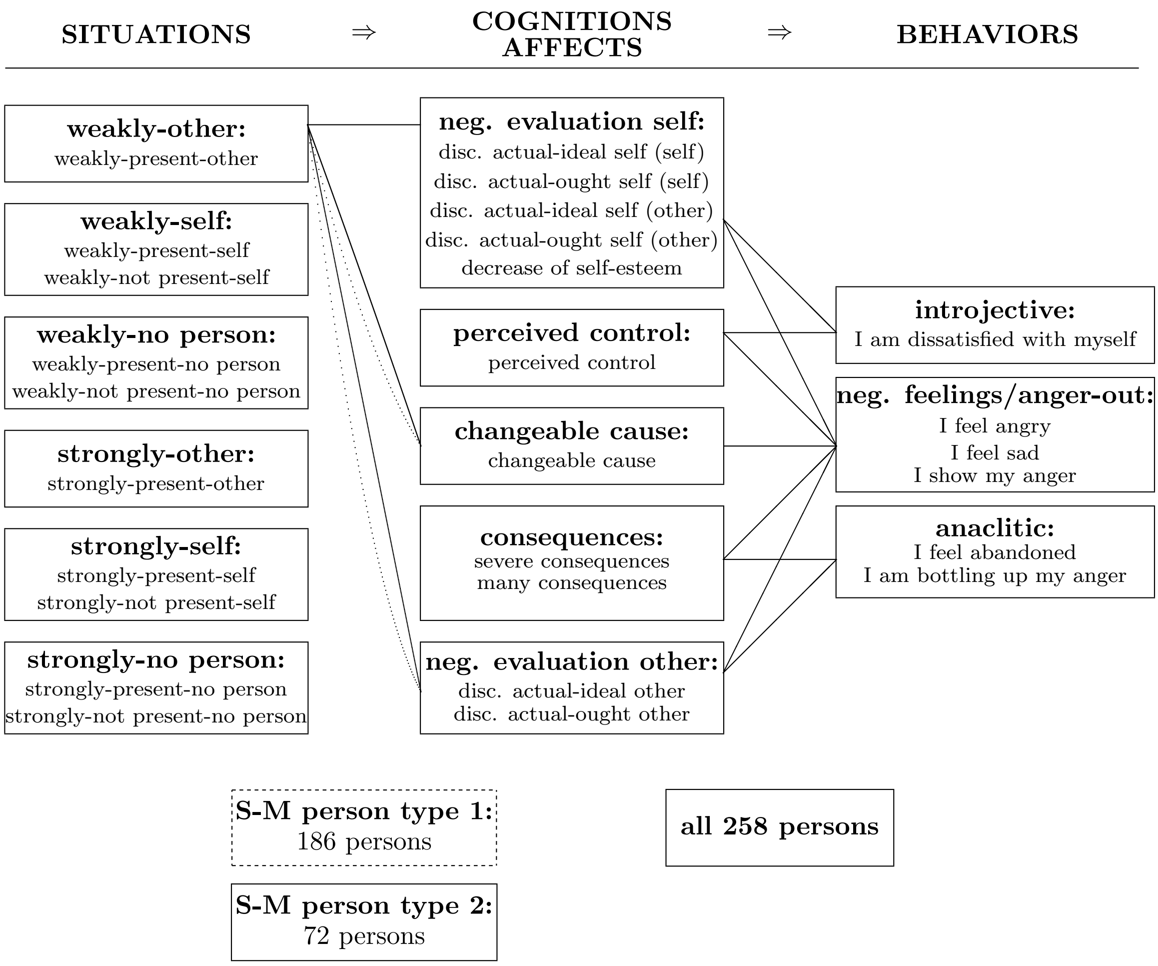

Figure 4: Graphical representation of the (6,5,2,3,1) CLASSI model for the anger and sadness data. With respect to the S-M links, note that the figure only displays for the two S-M person types the *if* situation *then* cognition/affect type rules that start from the weakly-other situation type.

Figure 5: Graphical representation of the *if* situation type *then* cognition/affect type rules of the two S-M person types in the (6,5,2,3,1) CLASSI model for the anger and sadness data. The upper triangles in the boxes indicate whether (gray) or not (white) the corresponding *if* situation type *then* cognition/affect type rules hold for the first S-M person type PT_1^{S-M}, whereas the lower triangles represent the same information for the second S-M person type PT_2^{S-M}.

Table 3: Keywords for the 11 cognitions and affects in the graphical representation of the CLASSI solution for the anger and sadness data

Key words	Cognitions and affects
disc. actual-ideal self (self)	To what extent did you think that how you were deviated from how you ideally would like to be?
disc. actual-ought self (self)	To what extent did you think that how you were deviated from how you ought to be?
disc. actual-ideal self (other)	To what extent would a significant other person find that how you were in that situation deviated from how you ideally should be?
disc. actual-ought self (other)	To what extent would a significant other person find that how you were in that situation deviated from how you ought to be?
decrease of self-esteem	To what extent did the negative event decrease your self-esteem?
perceived control	To what extent did you have the feeling that you had control over what happened?
changeable cause	To what extent did you think that the cause of the negative event could be changed?
many consequences	To what extent did you think that the negative event would have consequences for many aspects of your life?
severe consequences	To what extent did you think that the consequences of the negative event would be severe?
disc. actual-ideal other	To what extent did the other person deviate from how (s)he ideally should be?
disc. actual-ought other	To what extent did the other person deviate from how (s)he ought to be?

and labeled the types in the same way. With respect to the S-M link, the selected CLASSI solution makes a distinction between two S-M person types PT_1^{S-M} and PT_2^{S-M}, containing 186 and 72 participants respectively. From the graphical representation of the *if* situation type *then* cognition/affect type rules of the two S-M person types in Figure 5, one may conclude that participants belonging to PT_1^{S-M} and PT_2^{S-M} mostly differ with respect to the evaluation of themselves and the other persons involved in the negative event: Whereas PT_2^{S-M} always evaluates both parties negatively, the evaluations made by PT_1^{S-M} depend on who caused the negative event. Regarding the M-R link, the selected (6,5,2,3,1) CLASSI solution implies only one M-R person type associated with a universal set of *if* cognition/affect type *then* behavior type rules. Inspecting the graphical representation of the selected CLASSI solution in Figure 4, this universal set can be summarized as follows: Whereas each of the cognition/affect types elicits negative feelings and the anger-out response, 'negative evaluation of self' and 'perceived control' give rise to the introjective response and 'negative evaluation of other' and 'consequences' make a person display anaclitic behavior.

With respect to the two important CAPS questions mentioned above, one may conclude that (1) all included cognitions and affects mediate between some of the situations and behaviors under study, and (2) individual differences in negative situation-anger/sadness behavior profiles are fully accounted for by individual differences in the situation-cognitions/affects link.

6 Discussion and conclusion

In this paper, we proposed the novel CLASSI model, which was explicitly designed for studying individual differences in sequential processes. In particular, the key principle of CLASSI consists of reducing the stimulus (S), mediating variable (M), and response (R) nodes of a sequential process to a few mutually exclusive types and inducing a S-M and a M-R person typology from the data, with the S-M person types being characterized in terms of *if* S type *then* M type rules and the M-R person types in terms of *if* M type *then* R type rules. As such, the number of S-M and M-R person types and the extent to which their associated if-then rules differ, indicates whether important individual differences occur in the S-M and M-R links of the sequential process under study. As sequential processes are the corner stone of many psychological theories - the Cognitive Affective Personality System (CAPS) theory (Mischel & Shoda, 1995, 1998), the appraisal theory of emotion (Scherer, 2001), and the theory of planned behavior (Ajzen, 1991) are a few examples -, CLASSI analysis is widely applicable in psychological research.

In the remainder of this section, we relate CLASSI to other methods and we discuss possible extensions of the CLASSI method.

6.1 Relation to other methods

The relationships of the CLASSI method to other methods can be considered on the level of the submodels for reconstructing $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$ respectively as well as on the level of the global CLASSI model.

Regarding the *submodels* of the CLASSI model, it has been stated in section 2.2 that rule (1) for reconstructing data array $\underline{\mathbf{X}}^M$ is equivalent to the decomposition rule of a constrained three-mode partitioning model, the constraint implying that the S-M linking array $\underline{\mathbf{L}}^{S-M}$ is restricted to be binary. In turn, the submodel for reconstructing $\underline{\mathbf{X}}^R$ is a constrained multiway multivariate (Boolean) regression model with L criterion variables and Q predictor variables. It is a multiway model in that the criterion and predictor values can be organized into a binary $L \times I \times K$ criterion by stimulus by person criterion array and a binary $Q \times I \times K$ predictor by stimulus by person array; also, the (binary) regression weights depend on both the criterion and the person under study and can as such be organized into a (binary) $Q \times L \times K$ predictor by criterion by person regression weight array. Moreover, the model is constrained in that it puts a rank constraint on the regression weight array. In particular, the L criteria and the K persons are reduced to S criterion types and T person types, implying that the binary regression weights have the same value for criteria belonging to the same criterion type and for persons belonging to the same person type.

The *global CLASSI model* is a model for two coupled binary three-way three-mode data arrays. As such, the CLASSI approach bears clear resemblances to the multiway covariates regression approach in the area of real-valued three-way three-mode component analysis (Smilde & Kiers, 1999), which is a method for analyzing coupled real-valued three-way three-mode data arrays. Yet, apart from the distinction between binary and real-valued data, CLASSI differs from multiway covariates regression in at least two respects. A first major distinction between the two methods involves their mathematical framework, with CLASSI being based on Boolean algebra and multiway covariates regression on linear algebra. Second, CLASSI was designed for analyzing data arrays that have two modes in common, that is, an $I \times J \times K$ stimulus by mediating variable by person data array and an $I \times L \times K$ stimulus by response by person data array that have the stimulus and person modes in common. Multiway covariates regression is intended for data arrays that have only one mode in common, for instance, an $I \times J \times K$ negative event by negative emotion by person data array and an $L \times M \times K$ positive event by positive emotion person data array that have the person mode in common.

6.2 Possible extensions of the CLASSI method

Possible extensions of the CLASSI method can be considered on the level of the data, the level of the model, and the level of the data analysis.

Regarding the level of the *data*, to study some sequential processes, it is indicated to gather real-valued data instead of binary data. For instance, in emotion psychology, one is often interested in the intensity with which emotions occur in specific situations rather than in their presence/absence. Hence, one may consider to extend the CLASSI model to real-valued data. Such an extension, however, would require the replacement of the discrete framework of Boolean matrix algebra by a continuous mathematical framework, as well as the development of novel types of algorithmic approaches.

Regarding the level of the *model*, some psychological theories postulate sequential processes with more than two links, implying that the presence/absence of one set of mediating variables depends itself on the presence/absence of another set of mediating variables. For instance, in componential theories of emotions, which shed light on how specific situations may elicit particular emotions, one often assumes that situation-emotion profiles are mediated by appraisals (i.e., the outcome of cognitive evaluations of the situation) on the one hand and action tendencies on the other hand (see, e.g., Frijda, Kuipers, & Schure, 1989):

$$\text{situation} \Rightarrow \text{appraisals} \Rightarrow \text{action tendencies} \Rightarrow \text{emotion.}$$

To study in which link(s) of the latter sequential process important individual differences occur, the CLASSI model has to be extended to include more than two links.

Regarding the level of the *data analysis*, an inspection of the CLASSI loss function (4) reveals that the entries of the data arrays $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$ are given equal weight in the data analysis. However, in some cases it may be desirable to attach more importance to the correct reconstruction of one of these data arrays, for example, because the information in one data array was gathered in a more reliable way than the information in the other data array. To include such information about the quality of the two data arrays in the data analysis, one may introduce a weight parameter α in the CLASSI loss function that indicates the weight that is given to the correct reconstruction of $\underline{\mathbf{X}}^M$ and $\underline{\mathbf{X}}^R$:

$$L = \alpha \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} (x_{ijk}^M - \hat{x}_{ijk}^M)^2 + (1-\alpha) \sum_{i=1}^{I} \sum_{l=1}^{L} \sum_{k=1}^{K} (x_{ilk}^R - \hat{x}_{ilk}^R)^2, \tag{9}$$

where $0 \leq \alpha \leq 1$ (see, e.g., Smilde & Kiers, 1999). The value of this weight parameter α can be set by the data analyst or can be selected by means of cross validation techniques

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