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Toward an Integrative Psychometric Model of Emotions

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Abstract

Emotions are part and parcel of the human condition, but their nature is debated. Three broad classes of theories about the nature of emotions can be distinguished: affect-program theories, constructionist theories, and appraisal theories. Integrating these broad classes of theories into a unifying theory is challenging. An integrative psychometric model of emotions can inform such a theory because psychometric models are intertwined with theoretical perspectives about constructs. To identify an integrative psychometric model, we delineate properties of emotions stated by emotion theories and investigate whether psychometric models account for these properties. Specifically, an integrative psychometric model of emotions should allow (a) identifying distinct emotions (central in affect-program theories), (b) between- and within-person variations of emotions (central in constructionist theories), and (c) causal relationships between emotion components (central in appraisal theories). Evidence suggests that the popular reflective and formative latent variable models—in which emotions are conceptualized as unobservable causes or consequences of emotion components—cannot account for all properties. Conversely, a psychometric network model—in which emotions are conceptualized as systems of causally interacting emotion components—accounts for all properties. The psychometric network model thus constitutes an integrative psychometric model of emotions, facilitating progress toward a unifying theory.

Keywords

emotion, reflective latent-variable model, formative latent-variable model, psychometric network model

What is an emotion? This question has dominated emotion research since its very beginning (James, 1884). Yet, over a century later, the answer to this question remains elusive, as definitions and conceptualizations of the emotion construct vary greatly between theoretical approaches. Emotions have, for example, been conceptualized as evolutionarily basic affect programs (e.g., Ekman & Cordaro, 2011; Izard, 2007), social and cultural constructions of the mind (e.g., Barrett, 2014; Mesquita & Boiger, 2014), and multicomponent processes driven by appraisals of the situation (e.g., Lewis, 2005; Scherer, 2009). Each of these approaches has advanced emotion research. But it is challenging to integrate these approaches into a unifying theoretical perspective on emotions, even though such integration is desired for the sake of parsimony and to counteract the current fragmentation of the literature (Moors, 2017; Russell, 2015). In fact, many broad theories of emotions are often framed as being largely inconsistent with or independent from one another (see, e.g., Barrett, 2006). In addition, empirical research within one theory is rarely aimed at testing alternative emotion theories. As a result, research on central properties that define emotions has become fragmented into isolated strands that largely operate within their own research tradition, impeding a comprehensive and unified understanding of emotions.

We argue that integrating these disparate theoretical perspectives can be facilitated by identifying an integrative psychometric model of emotions. Psychometric models and theoretical perspectives about psychological constructs are intertwined; in fact, one could maintain that any psychometric model depends on a (possibly

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minimal) theory of the construct because it necessarily specifies the way the construct relates to observations (Borsboom, 2005; Edwards & Bagozzi, 2000; see also Greenwald, 2012). For instance, measuring an emotion by averaging questionnaire items that represent different emotion components (e.g., thoughts, feelings, action tendencies) is justifiable if one assumes that all components are indicators of the same underlying emotion, which, for instance, acts as a common cause with respect to each of them (e.g., an affect program). Alternatively, measuring only the valence of an affective state implies that there are no distinct emotions, or at least that these are not considered relevant. Because psychometric models and theoretical perspectives are intertwined, an integrative psychometric model may contribute to integrating emotion theories.

Which psychometric model could possibly constitute an integrative model for emotions? We take two steps toward answering this question. First, we identify the central properties of emotions, on the basis of three broad classes of emotion theories, that an integrative psychometric model of emotions has to account for. That is, we identify established findings in the emotion literature that we think need to be integrated in any unifying theory of emotions. Second, we investigate which psychometric model accounts for these properties. Specifically, we review evidence pertaining to whether the theoretical implications of the commonly applied *reflective latent*—in which emotions are conceptualized as unobservable variables that cause emotion components—and *formative latent-variable model*—in which emotions are conceptualized as unobservable variables that are caused by emotion components—align with evidence accumulated across emotion theories, because both latent-variable models fail to account for all properties, we introduce a novel psychometric model for emotions—the *psychometric network model*—in which emotions are conceptualized as systems of causal interactions between emotion components.

Emotion Theories

The first step toward an integrative psychometric model of emotions is to identify the necessary properties of such a model from the perspective of different emotion theories. Three broad classes of theories about the nature of emotions have been identified that each cover a larger number of more specific theories (Moors, 2012): affect-program theories, constructionist theories, and appraisal theories. Note that there is consensus across theories that emotions can be defined as entailing a number of components; that is, emotions entail changes in subjective feelings (e.g., arousal), cognitions (e.g., beliefs), action tendencies (e.g., goals), expressive behaviors (e.g., facial display), and physiology (e.g., hormonal changes). Moreover, the theories agree that emotions have antecedent events (e.g., a situation that is relevant to one's goals) and are directed at an object (e.g., another person).

The theories differ, however, in how they conceptualize the relation between emotions and their components. Moreover, they present different hypotheses on how antecedent events elicit emotions. Therefore, these theoretical conceptualizations highlight different properties of emotions (i.e., established characteristics of emotions). We describe what we consider the fundamental properties these theories ascribe to emotions and that, consequentially, need to be accounted for by an integrative psychometric model. We acknowledge that within the three broad classes of emotion theories there is variation in the emphasis on the fundamental properties and their relations. Moreover, specific theories within each broader class sometimes postulate additional properties that overlap with fundamental properties ascribed to emotions by theories of the other broad classes. Yet we argue that each broad class of emotion theories emphasizes one property over others. Thus, we delineate properties that are shared and emphasized by most approaches or research lines within each class of theories.

Affect-program theories

Affect-program theories originated from research on facial expressions of emotions. Most of these theories postulate that certain affect programs are triggered in evolutionarily important situations by specific stimuli (e.g., Ekman, 1993; Ekman & Cordaro, 2011; Izard, 2007). The affect programs are often equated with distinct neural signatures (Ekman, 1992, 1999; see also Buck, 1999; Panksepp, 2007). Typical theorizing proposed that, once triggered, an affect program automatically elicits the emotion components (Levenson, 1994). These components are considered to be coherent, functional responses to the respective situation (Tracy, 2014). For instance, in one approach, anger is conceptualized as an emotion that is elicited when someone or something is blocking a personal goal (Ekman & Cordaro, 2011). This percept activates the left inferior frontal gyrus (Vytal & Hamann, 2010). The anger affect program can elicit, for instance, high arousal (Russell, 1980), aggressive thoughts (Berkowitz, 1990), frowning (Elfenbein & Ambady, 2002), and motivation to attack the other person (Fischer & Roseman, 2007). All of these components functionally cohere to unblock the person's goal.

According to affect-program theories, the number of distinct emotions is limited. Given the mapping of affect programs to neural signatures, the number of emotions is often restricted to the number of unique neural signatures (Ekman, 1999), but it is also defined via distinctiveness in terms of expressive signals, antecedent events, intensity profiles, or existence in other primates (Ekman & Cordaro, 2011). These emotions are called basic (e.g., happiness, disgust, fear, anger) because they can be found across cultures and species. Most theories argue that nonbasic emotions (e.g., shame, regret) may arise as blends or derivatives of basic emotions (Buck, 1999; Oatley & Johnson-Laird, 1987; Panksepp, 2007).

The central aim in affect-program research consists in identifying the neural or biological basis of distinct emotions and their components (Ekman, 1999) and in specifying how distinct emotions can be distinguished on the basis of their adaptive value (Frijda, 2007; Izard, 1992). For instance, common questions are whether anger has distinct facial, postural, or vocal expressions that can be recognized across different cultures (e.g., Ekman, Sorenson, & Friesen, 1969; Sauter, Eisner, Ekman, & Scott, 2010) and how anger is different from similar emotions such as contempt with respect to its emotion components and social functions (e.g., Fischer & Giner-Sorolla, 2016; Fischer & Roseman, 2007). The assumption is that each distinct emotion can be characterized by a pattern of component changes that is at least partly unique compared with other emotions. This research eventually leads to long lists (Scherer, 2005) or highly branched hierarchies of distinct emotions (e.g., Plutchik, 1982; Shiota et al., 2017) that are all studied separately or in combination (Weidman, Steckler, & Tracy, 2017).

Evidence within affect-program theories supports the notion that a number of components can be used to distinguish emotions from each other. Emotions differ from each other, because the patterns of changes in components they entail are at least partly distinct from each other (Ekman & Cordaro, 2011). Some of these distinct features are even shared across cultures (Elfenbein & Ambady, 2002). This distinctiveness may ultimately underpin the broad adaptive value of emotions because changes in different components facilitate targeted responses to specific situations (Tracy, 2014). Therefore, we propose that the first property of emotions that an integrative psychometric model needs to account for, as suggested by affect-program theories, is that it allows for the identification of distinct emotions.

Constructionist theories

Constructionist theories do not conceptualize emotions as uniform affect programs with a specific signature. Instead, they typically conceptualize them as emergent phenomena (Barrett, 2006, 2012) that are constructed from domain-general mechanisms, that is, mechanisms that also contribute to other functions beyond emotions (Gray, Schein, & Cameron, 2017; Lindquist, 2013). Specifically, in many variants, constructionist theories state that humans continuously experience varying core affect (Kuppens, Oravecz, & Tuerlinckx, 2010), defined as a combination of valence and arousal (Russell, 1980). One central constructionist theory holds that core affect can change abruptly as a result of external stimuli (Russell, 2003, 2009). If such changes are attributed to the external stimuli, this leads to a variety of changes in various components. These changes constitute an *emotional episode*. Another theory holds that emotions can be constructed on the basis of endogenously (i.e., internally) generated affect (Lindquist, Satpute, & Gendron, 2015). Across constructionist theories, emotions are then typically argued to emerge from humans' tendency to categorize and essentialize these sensations as an emotion. For instance, emotions become real in a person's mind as a result of the application of conceptual knowledge, which is used to label them (Barrett, 2014; Lindquist, Gendron, Oosterwijk, & Barrett, 2013; Schachter & Singer, 1962), or emotions result from and, in turn, shape social situations (Mesquita & Boiger, 2014).

According to these theories, the construction process is based on culturally learned schemas and situational influences. Therefore, different people may indicate that they experience the same emotion even though the elicitation process was different, or emotion components manifest themselves differently. For instance, in the United States and Belgium the most frequent appraisal eliciting anger is the perception that *close others* block one's personal goals by violating *relationship norms*, whereas in Japan the most frequent appraisal underlying anger is the perception that *distant others* block one's personal goals by *being intentionally rude in social situations* (Boiger et al., 2018). The elicited anger experience is then also characterized by different emotion components between different persons (Averill, 1983). Therefore, in principle, there is an infinite number of possible affective states, rendering it meaningless to search for distinct components uniquely connected to distinct emotions. Instead, emotions are more easily arranged according to their location in a multidimensional space, specified, for instance, by valence, arousal, or potency (e.g., Fontaine, Scherer, Roesch, & Ellsworth, 2007; Russell, 1980; Watson, Clark, & Tellegen, 1988; Wundt, 1887). According to most constructionist theories, different cognitions then contribute to disambiguating the situation (Lindquist, 2013; Russell, 2003; Schachter & Singer, 1962).

The central aim in research within the framework of constructionism is to explain variation within seemingly distinct emotions across persons and/or within persons across time (Cunningham, Dunfield, & Stillman, 2013; Lindquist, 2013). For instance, common questions are how emotions vary across cultures (De Leersnyder, Mesquita, & Boiger, in press; Mesquita & Frijda, 1992), how the same emotional face can be interpreted in many different ways (Crivelli, Russell, Jarillo, & Fernández-Dols, 2016), how personality affects the experience of emotions (Kuppens & Tong, 2010), or how the same states can be labeled with different emotion labels and different states with the same label (Lindquist & Barrett, 2008; Lindquist et al., 2015; Schachter & Singer, 1962).

Evidence in line with constructionist theories supports the notion that emotions can take various forms across persons and even across situations within the same person. Each emotion may entail different patterns of changes in emotion components for different persons (Kuppens & Tong, 2010). Moreover, in different situations, the very same emotion may entail different patterns of changes for the same person (Averill, 1983). This implies that emotions are malleable states with fuzzy boundaries between them (Russell, 2003). That is, there is variation in how emotions manifest between and within persons. Therefore, we propose that the second property of emotions that an integrative psychometric model needs to account for, as suggested by constructionist theories, is that it allows for both between- and within-person variation in emotions.

Appraisal theories

Appraisal theories encompass a multitude of different perspectives explaining the relation between an event and the elicitation of specific emotions. Across these theories, appraisals are defined as continuous evaluations of encountered stimuli on dimensions such as novelty, valence, goal conduciveness, agency, or compatibility with norms and values (Ellsworth & Scherer, 2003). These evaluations contribute to the elicitation and subsequent regulation of emotions. Originally, many affect-program theories considered patterns of appraisals to be the cause of the activation of affect programs (e.g., Ekman, 1999; Lazarus & Smith, 1988; Roseman, 2013; Smith & Ellsworth, 1985). In other words, once a stimulus is evaluated according to a specific pattern of appraisal dimensions, a distinct emotion would be elicited. For instance, in most approaches, anger is elicited when an event is appraised as novel, goal-obstructive, very likely to occur, urgent, and caused by others but controllable by one's own actions (e.g., Ellsworth & Scherer, 2003).

More recent appraisal theories conceptualize the relation between appraisal and emotion differently (Moors, 2014). They no longer relate appraisal patterns to affect programs. Instead, individual appraisals are theorized to cause other individual emotion components, such as action tendencies. Once these components are elicited, they collectively emerge as the content of the feeling component (e.g., "I feel so mistreated and would like to hit this person in the face"), and, finally, the sum of all components emerges as an emotion. The emotion can potentially become conscious and then also be categorized or verbalized. These newer appraisal theories mainly differ from one another in how the relation of appraisals and emotion components is conceptualized. In some theories, appraisals sequentially determine different emotion components (Scherer, 2009). In other variants, the process follows a dynamic systems approach involving various feedback loops (Lewis, 2005; Lewis & Liu, 2011; Thagard & Nerb, 2002) or is more strongly situated (Clore & Ortony, 2013; Ortony & Turner, 1990).

As appraisals are linked directly to emotion components, there is more variation with respect to how an emotion evolves. Each appraisal involved in the elicitation of anger, for instance, is theorized to cause some of anger's components. As examples, in one theory, the appraisal of goal obstruction increases preparation for action, respiration, and heart rate, as well as frowning, whereas controllability appraisals increase blood pressure or narrow the eyes (Scherer, 2009). Differences with respect to these appraisals may lead to different subjective experiences (Ortony & Turner, 1990). Therefore, the reasoning of most appraisal theories is that there are as many emotions as there are appraisal patterns. Nevertheless, specific appraisal patterns are often theorized to be frequently encountered because they stem from recurrent situations. These frequent patterns may lead to modal emotions reminiscent of basic emotions (Scherer, 2009). However, these modal emotions are typically theorized to emerge from the changes caused by appraisal patterns rather than from affect programs (Sander, Grandjean, & Scherer, 2018).

The central aim of research applying appraisal theories is to investigate the causal role of appraisal dimensions in the elicitation of other emotion components (Scherer, 2009; Scherer & Moors, 2019). Common questions are how appraisals such as agency are linked to physiological reactions (Smith, 1989), how appraisals relate to action tendencies (Frijda, Kuipers, & ter Schure, 1989), at which time point different appraisals affect emotion evolvement (Grandjean & Scherer, 2008), or whether appraisals have causal effects in the first place (Parkinson, 1997). In addition, studies also aimed at distinguishing multiple emotions by comparing them in terms of patterns of changes on appraisal dimensions (Roseman, Antoniou, & Rose, 1996; Smith & Ellsworth, 1985).

Evidence in line with appraisal theories supports the notion that different emotion components causally interact with each other. Although appraisal theories mainly focus on the causal role of appraisal dimensions (Frijda et al., 1989; Scherer & Moors, 2019), each emotion component also conversely affects appraisals and other components (Lewis, 2005). These interactions then contribute to the unfolding of an emotion episode in a specific situation (Clore & Ortony, 2013). Therefore, we propose that the third property of emotions that an integrative psychometric model needs to account for, as suggested by appraisal theories, is that it allows for causal relationships between a multitude of emotion components.

Summary

We argue that an integrative psychometric model of emotions must account for at least three properties that reflect fundamental insights about the nature of emotions derived from the three broad classes of emotion theories. First, in line with affect-program theories, an integrative psychometric model of emotions should allow identifying distinct emotions. Second, in line with constructionist theories, it should allow between- and within-person variation in emotions. Third, in line with appraisal theories, it should allow identifying causal relationships between a multitude of emotion components.

Psychometric Models of Emotions

Having identified the properties an integrative psychometric model of emotions must account for, the second step is to identify a model that accounts for these properties. Psychometric models describe the relation of observable properties, such as behaviors or item responses, to a theoretical construct. Most basically, it has been argued that they are only means of data reduction (e.g., Jonas & Markon, 2016). However, to justify the use of psychometric models as models that are designed to *measure* specific psychological constructs (rather than merely descriptive relations in data), the relationships in psychometric models (e.g., between indicators and latent variables) are best considered causal (e.g., Bollen & Lennox, 1991; Borsboom, Mellenbergh, & van Heerden, 2003; Edwards & Bagozzi, 2000). Thereby, these models function not only as practical operationalizations but also as construct theories that explicate otherwise often vague conceptualizations and therefore make broader theories including these constructs more unequivocally testable (Markus & Borsboom, 2013). Put differently, an integrative psychometric model of emotions can and should inform a substantive theory of emotions that facilitates further research on emotions.

Three psychometric models are particularly relevant to psychological science. Traditionally, the two most prominent models in psychology have been the *reflective* and *formative latent-variable models* (Bollen & Lennox, 1991; Schmittmann et al., 2013), which have also been proposed as psychometric models of emotions (Coan, 2010). More recently, a third model has been proposed: the *psychometric network model* (e.g., Borsboom, 2008; Schmittmann et al., 2013). This alternative model has not yet been applied to emotions. Below we analyze the compatibility of each of these models with the required properties posed by the broad classes of emotion theories. By doing so, we follow an abductive scientific method (Haig, 2005). Specifically, we start with an established set of phenomena related to a construct (i.e., the properties of emotions) and try to identify a plausible theory (i.e., a psychometric model) that accounts for these phenomena. If the model can be applied to the construct, evidence is in line with the model's implications. For instance, whether emotions can be modeled as reflective latent variables can be determined by comparing the theoretical implications of the model for the nature of emotions with evidence accumulated across emotion theories.

The reflective latent-variable model

In the reflective latent-variable model, psychological constructs are conceptualized as unobservable (i.e., latent) variables that can be assessed through multiple observable indicators. Applied to emotions, the idea is that an emotion cannot be observed directly. What one can observe, however, are the different components associated with the emotion. In the reflective latent-variable model, the emotion is thus conceptualized as causing changes in these various emotion components. For instance, anger is conceptualized as an unobservable variable that causes changes in arousal, aggressive thoughts, frowning, and motivation to attack (Fig. 1).

Formally, the reflective latent-variable model comprises a set of equations in which each indicator is a function of the latent variable (Jöreskog, 1971). As depicted in Figure 1, the latent emotion is linked with coefficient λ_i to a given emotion component *i*. This coefficient constitutes a linear function that describes the relation between the emotion component and the emotion (analogous to a regression weight taken from a linear regression of one emotion component on the emotion). Unexplained variance, δ_i, captures all causes of the respective emotion component that is not accounted for by the emotion (Bollen & Pearl, 2013). This residual is assumed to be uncorrelated with the emotion and with other residuals.

In a study following the logic of the reflective latent-variable model, a researcher can assess the components

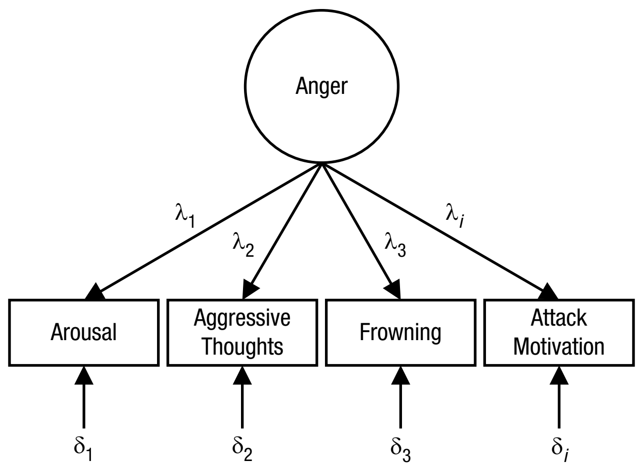

Fig. 1. Illustration of a reflective latent-variable model of anger. Anger is a latent (i.e., unobserved) variable that causes multiple emotion components. λ_i denotes the effects of anger on the emotion components. δ_i denotes variance unexplained by anger in the emotion components (i.e., residual).

of a specific emotion. For instance, to measure anger, a researcher could administer a questionnaire with items assessing the participant's arousal, aggressive thoughts, frowning, and motivation to attack (each component could of course also be assessed in other ways). Once data for each component have been gathered, the model as depicted in Figure 1 can be tested with confirmatory factor analysis.

This analysis, however, is uncommon in emotion research. Instead, researchers tend to use two alternative strategies, at least when it comes to self-reports (Weidman et al., 2017). First, given that all emotion components are conceptualized as indicators of anger, their scores can be averaged or summed to serve as an approximate estimate of the intensity of the emotion (e.g., Spielberger, 1988). Second, researchers commonly ask directly how angry participants are (e.g., Halmburger, Baumert, & Schmitt, 2015), assuming that they can integrate the various emotion components themselves. Therefore, the reflective latent-variable model may underlie research on emotions, even if it is not explicitly tested.

The reflective latent-variable model is the psychometric model underlying most psychological research (Borsboom et al., 2003), including research on emotions (Coan, 2010). But does it constitute an integrative psychometric model of emotions such that it accounts for the three properties (i.e., distinct emotions, variation between and within persons, causal relationships between components) required by affect-program theories, constructionist theories, and appraisal theories?

The reflective latent-variable model and the property of distinct emotions. The reflective latent-variable model has two implications that describe how distinct emotions could be understood (Table 1). The first implication is that, if the reflective latent-variable model were true, the latent variable should designate a *common cause* of its indicators (Borsboom, 2008; Borsboom et al., 2003). As depicted in Figure 1, the latent variable (i.e., the emotion) causes changes in all indicators (i.e., the emotional components). Many scholars think that there must be a manifestation such as a brain module whose activity causes the indicators.[1] This notion of a common cause is equivalent to a *realist* interpretation of the latent variable, namely that the construct, as represented in the model by a latent variable, actually refers to a real entity that functions as a common cause of the indicators. Under this interpretation, common psychometric practices (e.g., interpreting average test scores as reasonable representations of a hypothetical construct) are scientifically justifiable.

The idea that specific neural signatures for distinct emotions identify common causes of emotion components is also a central proposition in affect-program theories (Ekman, 1999). However, the evidence for such specific neural signatures is mixed. Research based on animals and humans supports the conclusion that different affective states (i.e., broad affective response systems such as approach, agonism, or hunger) map onto different neural signatures (Buck, 1999; Panksepp, 2007). However, in these studies, distinct emotions are related to a complex interplay of brain activation, receptor systems, peptide neurohormones, and enzymes. In fact, a meta-analysis of brain research on emotions supports that emotions cannot be uniquely localized in specific brain areas (Lindquist, Wager, Kober, Bliss-Moreau, & Barrett, 2012). Thus, even if distinct emotions did have unique neural signatures (which is doubtful), it seems unlikely that these signatures constitute common causes. Instead, the neural basis of emotions can be conceived of either in terms of interactions of multiple domain-general mechanisms, which also contribute to numerous other (psychological) processes (Cunningham et al., 2013; Dalgleish, 2004; Lindquist, 2013; Ortony & Turner, 1990), or in terms of dynamic, context-dependent interactions of various brain regions (Lewis, 2005; Pessoa, 2017; Sander et al., 2018).

A second implication of the reflective latent-variable model relevant for the property of distinct emotions is that if the relationship between the latent variable and the indicators is indeed causal then the latent variable and its indicators are *separately identifiable* (Borsboom et al., 2003); the reason for this is that current theories of causality require causes and effects to be distinct (i.e., "A causes A" is not a viable proposition). As depicted in Figure 1, the emotion is something separate from its components. Yet, for emotions, it is difficult to imagine a state such as anger as ontologically independent from

Table 1. Implications of Each Psychometric Model That Refer to the Respective Property of Emotions as Posed by Three Classes of Emotion Theories

Properties of emotions posed by emotion theories	Psychometric model		
	Reflective latent variable model	Formative latent variable model	Network model
Distinct emotions (posed by affect-program theories)	*Common-cause relation* • A single cause exists that predicts all components → Contradicted by empirical evidence	*Interpretational confounding* • Meaning of emotion is a function of the external variable used to identify the model → Unreasonable for psychometric model	*Constitution* • Causal relationships constitute emotion → Supported by empirical evidence
	Separate identifiability • The emotion and its components are separate entities → Implausible	*Exhaustive sets of indicators* • All components must be measured → Requires theorizing	*Exhaustive sets of indicators* • All components must be measured → Requires theorizing
Variation between and within persons (posed by constructionist theories)	*Local homogeneity assumption* • Model has the same form between and within persons → Contradicted by empirical evidence	*Local homogeneity and heterogeneity* • Model can vary between and within persons → Supported by empirical evidence	*Homogeneity and heterogeneity* • Model can vary between and within persons → Supported by empirical evidence
Causal relationships between components (posed by appraisal theories)	*Principle of local independence* • Correlated components become independent when controlling for the emotion → Contradicted by empirical evidence	*External relationships* • Relationships between components are uninformative for meaning of emotion → Contradicted by empirical evidence	*Causal relationships* • Components have causal effects on each other → Supported by empirical evidence
	Assumption of exchangeability • Components are redundant → Contradicted by empirical evidence		

Note: In each cell of the table, we summarize which implications of the respective psychometric model are relevant for the respective required properties of emotions mentioned in the row. The key points marked with bullets constitute short descriptions of the implications as applied to emotions. The key points marked with arrows indicate whether these implications are supported for emotions.

its components. What would anger look like if one removes arousal, aggressive thoughts, the motivation to attack, and frowning?

The inseparable nature of emotions and their components is also reflected in the fact that emotions are often manipulated and measured via their components instead of the emotion and its components being manipulated separately (Moors, 2017). For instance, anger has been manipulated by letting people frown and then measuring subjective feelings (e.g., Duclos et al., 1989; Kuppens, Van Mechelen, Smits, & De Boeck, 2003) or by instructing participants to contract the facial muscles that produce the expression of anger and measuring physiological reactions (Ekman, Levenson, & Friesen, 1983). These approaches are inconsistent with the reflective latent-variable model. This is because, under this model, the causal paths lead only from the latent emotion to the components, not from one component to another. Thus, under the common-cause interpretation of the latent-variable model, many standard experimental manipulations—which are routinely used in research on emotions—would be impossible.

Another strategy may seem to be more in line with the reflective latent-variable model. Namely, emotions have often been manipulated separately from their components by asking participants to recall an incident of a particular emotion. For instance, participants may be asked to recall an incident of anger and then respond to a number of questions assessing various emotion components of anger (e.g., Fischer & Roseman, 2007). However, we deem it more likely that participants recall a situation that fits their conception of anger on the basis of several emotion components (i.e., the common meaning of the word *anger*) than that they recall an emotion independent from its components. As such, there appears to be neither theoretical nor empirical support for separate identifiability.

In short, the conceptualization of distinct emotions is possible in the reflective latent-variable model. However, evidence contradicts the implications that emotions are separately identifiable common causes of their components. This means that the reflective latent-variable model cannot satisfactorily account for the required property to identify distinct emotions.

The reflective latent-variable model and the property of variation between and within persons. The reflective latent-variable model has one assumption that is relevant for the question of whether it allows variation between and within persons (Table 1). This relates to the *local homogeneity assumption* (Borsboom et al., 2003; Ellis & Van den Wollenberg, 1993; see also Hamaker, Dolan, & Molenaar, 2005; Molenaar & Campbell, 2009), which holds that the psychometric model applies not only to the individual differences in the population but also at the level of the individual. Put differently, the estimated model is assumed to apply to all individuals in the population, as if all individuals are identical. This makes sense from a causal perspective: If a latent variable acts as a common cause of the indicators, the resulting psychometric model should be expected to have the same form between and within persons, because in that case within-person differences and between-person differences in the indicators have the same causal background (Weinberger, 2015). This assumption follows naturally if the common cause of the indicator variables is assumed to exist in each person, causing uniform effects. For instance, if activity of a universal brain module acts as a common cause of all indicators, then its effects would be uniform across individuals.

For emotions, this implies that if the locally homogeneous reflective latent-variable model were true, then any unique pattern of components that characterizes an emotion should have the same form within and across persons—it has to be invariant. For instance, if, anger fuels a motivation to attack, it must do so for all people who experience anger. Moreover, it must do so for the same person across situations. As soon as the common cause is activated, the components of anger are activated as well. In the reflective latent-variable model, any deviations from these patterns should behave as measurement error, that is, represent variance that is irrelevant to the construct under investigation.

However, this is not supported by evidence. Just to provide some examples, research supports that people differ in how valence and arousal are related (Kuppens, Tuerlinckx, Russell, & Barrett, 2013), personality influences which appraisal dimensions elicit emotions and how exactly they relate to emotions (Kuppens & Tong, 2010), and the same emotion can relate to different appraisal dimensions across situations (Kuppens et al., 2003). In addition, there is ample evidence that cultural differences and social relationships in general shape the meaning and consequences of the same emotion (Averill, 1983; De Leersnyder et al., in press; Mesquita & Boiger, 2014; Mesquita & Frijda, 1992; Van Kleef, 2016). One way to reconcile these findings with the reflective latent-variable model might be to invoke additional (latent) variables that affect the emotion or the components (e.g., display rules), such as different causes for correlations among emotions between and within persons (Vansteelandt, Van Mechelen, & Nezlek, 2005). Given the large number of necessary additional (latent) variables that need to be invoked to explain all these findings as well as the ad hoc character of these modifications, a more sensible interpretation is that conceptualizations of the same emotion simply vary between and within persons. This directly contradicts the local homogeneity assumption. Thus, given a causal interpretation of the reflective latent-variable model, it cannot satisfactorily account for the required property of between- and within-person variation.

The reflective latent-variable model and the property of causal relationships between components. The reflective latent-variable model has two implications that are important for the question of whether it allows direct causal relationships between emotion components (Table 1). They are called the *principle of local independence* (Borsboom, 2005, 2008; Borsboom et al., 2003) and the *assumption of exchangeability* (Bollen & Lennox, 1991; Borsboom, 2008; Borsboom et al., 2003). Specifically, as the indicators are all caused by the latent variable, they change in an identical fashion once the latent variable changes (except if there is measurement error). For instance, once the brain module is activated, all indicators change accordingly. When the indicators all change in an identical fashion, this means their statistical behavior satisfies a form of exchangeability (Junker & Ellis, 1997). Using multiple indicators to assess a latent variable merely increases the reliability of the measure by accounting for measurement error, but it does not change the nature of the latent variable. In fact, as all indicators change in an identical fashion, the information they provide is redundant. Moreover, as a consequence, the centrally controlled change leads to positive correlations among the indicators (Holland & Rosenbaum, 1986; Krijnen, 2004). Complementarily, when the latent variable is held constant, the indicators also do not change, and the correlations between them are assumed to disappear: The indicators become locally independent. Thus, in the reflective latent-variable model, indicators do not have direct causal effects on each other: The correlations among exchangeable indicators are spurious in the sense that they do not reflect a structural relation between the indicators themselves but are fully attributable to their dependence on a common cause.

Research contradicts these implications for emotions on two counts. First, empirical findings contradict the notion that the components of specific emotions are caused by a latent emotion such that they are all positively correlated. Specifically, in research on emotion coherence, correlations of multiple components of an emotion are usually moderate or even nonexistent, even if emotion components are properly measured (e.g., Reisenzein, 2000; Reisenzein, Bördgen, Holtbernd, & Matz, 2006; for a meta-analysis on the coherence of subjective feelings and facial expressions, see Duran, Reisenzein, & Fernández-Dols, 2017; for reviews on coherence, see Hollenstein & Lanteigne, 2014; Mauss & Robinson, 2009). Evidence shows that some components are correlated strongly only with a subset of other components (e.g., Evers et al., 2014; Mauss, Levenson, McCarter, Wilhelm, & Gross, 2005; for an overview, see Mauss & Robinson, 2009), something that, for instance, occurs for anger (Fischer & Roseman, 2007), envy (Lange, Weidman, & Crusius, 2018), and shame (Gausel, Leach, Vignoles, & Brown, 2012). Therefore, emotion components are also not exchangeable. Building on findings that support a lack of coherence of emotion components, we are not aware of any research that has tested whether these correlations among components disappear when controlling for the latent emotion in the reflective latent-variable model.

Second, evidence instead suggests that emotion components *do* have selective direct causal effects on each other. Most notably, research informed by newer appraisal theories shows that appraisal dimensions cause specific changes in other components (Scherer, 2009; Scherer & Moors, 2019). This additionally applies to relationships between other emotion components beyond appraisals (Lewis, 2005), as reflected, for instance, in multicomponential theories of specific emotions (e.g., Gausel et al., 2012; Lange et al., 2018). These direct causal effects among emotion components are at odds with the reflective latent-variable model.

Thus, the reflective latent-variable model cannot account for the required property that the emotion components can causally affect each other. Instead, in the model components are supposed to be independent, redundant indicators of the emotion. This conceptualization is inconsistent with the evidence.

Summary of the reflective latent-variable model. Evidence from emotion research indicates that the reflective latent-variable model does not fulfill the requirements of an integrative psychometric model of emotions (Table 1). First, it can theoretically account for the required property to identify distinct emotions as posed by affect-program theories. However, the conceptualization of distinct emotions in the reflective latent-variable model is not in line with empirical evidence. Specifically, evidence contradicts the implications of the model that all emotion components of a specific emotion have a separable common cause. Second, the reflective latent-variable model cannot account for the property of variation between and within persons as posed by constructionist theories. In fact, under the causal interpretation of the model, it even excludes such variation by definition because it treats emotions as locally homogeneous. Finally, the reflective latent-variable model cannot account for the property of allowing causal relationships between components as posed by appraisal theories. Specifically, the model instead conceptualizes the components as locally independent and exchangeable indicators of the emotion.

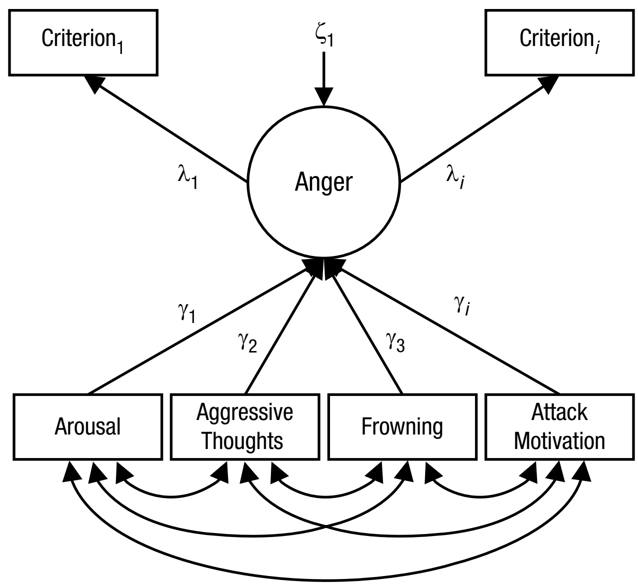

Fig. 2. Illustration of a formative latent-variable model of anger. Anger is a latent (i.e., unobserved) variable that is caused by multiple emotion components. γ_i denotes the effects of the emotion components on anger; λ_i denotes the effects of anger on the external variables necessary to identify the model; and ζ_1 denotes variance unexplained by the emotion components in anger (i.e., residual).

The formative latent-variable model

The formative latent-variable model also conceptualizes emotions as unobservable (i.e., latent) variables. What differentiates it from the reflective latent-variable model is that, in the formative model, the emotion components are conceptualized to cause changes in the emotion instead of the other way around. The underlying idea is that the emotion bundles information of the components. For instance, arousal, aggressive thoughts, frowning, and motivation to attack collectively cause anger (Fig. 2). Given that the formative latent-variable model constitutes a viable alternative to the reflective latent-variable model, the formative latent-variable model has also been proposed as a psychometric model of emotions (Coan, 2010; Coan & Gonzalez, 2015).

Formally, the formative latent-variable model constitutes an equation in which the latent variable is a function of all indicators (Bollen & Lennox, 1991). As depicted in Figure 2, each component i is linked with coefficient γ_i to the latent emotion. These coefficients constitute linear functions that describe the relation between the emotion and the emotion components (analogous to a linear regression of the emotion on all emotion components simultaneously). The emotion components can, but do not have to be, correlated; in the formative model, correlations between emotion components are allowed but treated as a nuisance (Schmittmann et al., 2013). Unexplained variance in the emotion, ζ_1, is typically taken to capture all causes of the emotion that are not accounted for by the emotion components. This residual is assumed to be uncorrelated with the components.

In a study following the logic of the formative latent-variable model, a researcher can again assess the components of a specific emotion. However, contrary to the reflective latent-variable model, the formative latent-variable model cannot be estimated without at least two external variables (i.e., consequences) that are predicted by the emotion (Bollen & Bauldry, 2011; MacCallum & Browne, 1993; Fig. 2). This is because there are not enough observed (co)variances in the data to estimate all the parameters in the model (i.e., the model is not identified). Put differently, there is not enough information to derive a unique solution for all parameters in the model. Multiple solutions would be possible, whereby the model is of little use. A researcher then needs to include additional variables to identify the model. For instance, the researcher could include multiple behaviors as consequences of the latent emotion variable. Set up this way, the latent anger variable serves as a bundle of the emotion components that mediates an effect on the external variables (e.g., the behaviors).

Testing such a model is uncommon in emotion research. Instead, the same strategies tend to be applied as for the reflective latent-variable model. That is, given that all emotion components are understood as collectively causing the emotion, their scores are often averaged as an approximate estimate of the emotion. Alternatively, researchers commonly ask how angry participants are, assuming they will integrate the components themselves. Therefore, the two most common ways of measuring emotions with self-reports, namely averaging components or using single items (Weidman et al., 2017), are broadly in line with latent-variable models but cannot distinguish between the reflective and formative models.

The question is again whether the theoretical implications of the formative latent-variable model fulfill the properties posed by the three broad classes of emotion theories. That is, the question is whether it allows identifying distinct emotions, variation between and within individuals, and causal relationships between components. Or to put it differently, is the formative latent-variable model an integrative psychometric model of emotions?

The formative latent-variable model and the property of distinct emotions. The formative latent-variable model differs in its conceptualization of distinct emotions from the reflective latent-variable model. It does not conceptualize emotions as common causes that are separately identifiable from their components. As emotions are caused by emotion components in the formative latent-variable model, the emotion represents an integrated representation of the emotion components. One interpretation would be that the emotion is constructed from the components (Borsboom, 2008; Borsboom et al., 2003; MacCallum & Browne, 1993) but is more than a composite of them (Bollen & Lennox, 1991). Moreover, each emotion component can be elicited by different elements of the environment (i.e., they can have their own causes), whereas the emotion is caused only by the components.

The formative latent-variable model has two other implications that are relevant for the property of distinct emotions (Table 1). The first implication is a consequence of the estimation of the formative latent-variable model. Because the formative latent-variable model can be estimated only when at least two external variables are added to the model, the crucial question is which external variables should be added. In the realm of emotions, a reasonable choice would be distal behaviors. As an example, anger toward a norm violator may increase the moral courage to do something about the violation (Halmburger et al., 2015), which could manifest in different behaviors. In addition to behavior, other external variables to identify anger are easily imaginable, such as status conferral (Tiedens, 2001), implicit evaluations (Mauss, 2006), or other affective states (Miceli & Castelfranchi, 2017).

The first implication of the formative latent-variable model that is relevant for the property of distinct emotions is a possible limitation of this multiplicity of potential external variables—*interpretational confounding* (Howell, Breivik, & Wilcox, 2007b). Interpretational confounding occurs when the latent emotion is not a reasonable bundle of the emotion components. For instance, arousal, aggressive thoughts, frowning, and motivation to attack all contribute to anger. Depending on the external variables used to estimate the formative latent-variable model, some components could become more predictive and others less. Therefore, under the formative latent-variable model, the meaning of the emotion may change according to which external variables are included in the model. For instance, if behavior is used as the external variable, components related to motivation may be most predictive, whereby anger could be mostly defined via motivations. If status conferral is instead used as the external variable, components related to facial expressions may be most predictive, whereby anger could be mostly defined via facial expressions. This characteristic of the formative latent-variable model is controversial and has led some people to question its usefulness as a psychometric model for psychological constructs in general (for a discussion, see Bagozzi, 2007; Bollen, 2007; Howell, Breivik, & Wilcox, 2007a; Howell et al., 2007b).

In the present context, there is no consensus in emotion research as to which external variables should be used. If different external variables are used across different studies for the same emotion, each study defines this emotion differently. These variable definitions preclude a shared meaning of the emotion across studies. Therefore, interpretational confounding at least partly undermines the identification of distinct emotions.

A second implication of the formative latent-variable model that is relevant for the property of distinct emotions is that it requires an *exhaustive set of indicators*. This means that excluding one indicator from the model changes the interpretation of the latent variable because the indicators collectively cause the part of the variance in the latent variable that predicts the external variables. For instance, if anger is defined via arousal, aggressive thoughts, frowning, and motivation to attack, all of these variables must be included to measure it adequately.

The selection of indicators, however, is challenging. It should be based on a priori theorizing. In research guided by affect-program theories, defining components of distinct emotions have been proposed (Ekman & Cordaro, 2011). In some cases attempts have been made to derive such comprehensive lists for specific emotions using theorizing (e.g., Fischer & Roseman, 2007) or data-driven approaches (e.g., Frijda et al., 1989; Lange et al., 2018; Shaver, Schwartz, Kirson, & O'Connor, 1987; Tracy & Robins, 2007; Weidman, Cheng, & Tracy, 2018; Weidman & Tracy, 2019). However, researchers use a variety of different emotion components to operationalize the same emotion, and the same emotion component is used to operationalize different emotions (Weidman et al., 2017). This indicates that there is no unequivocal consensus for many emotions.

Thus, in the formative latent-variable model, distinct emotions could be measured by linking exhaustive sets of components to multiple external variables via the emotion one intends to measure. Exhaustive lists of components are partly available and theorizing may foster the development of more such lists. However, the choice among multiple plausible external variables may lead to interpretational confounding. We therefore conclude that the formative latent-variable model fails to account for the required property to allow identifying distinct emotions.

The formative latent-variable model and the property of variation between and within persons. In the formative latent-variable model, the latent variable is not necessarily interpreted as constituting a distinct realist entity as in the reflective latent-variable model. Instead, the latent variable may alternatively be constructed from the indicators, which thereby define the construct (Borsboom, 2008; Borsboom et al., 2003). A specific emotion such as anger is then simply defined as an emotion that is constructed from arousal, aggressive thoughts, frowning, and, motivation to attack.

If the emotion components only define the construct, each emotion having its own cause, the model can vary between individuals. For some individuals, frowning may be an important contributor to anger, whereas for others it may not. Nevertheless, if frowning is defined as a component of anger, a frowning score should contribute to a measure of anger. Variation between people would not change any agreed on definition of anger. Therefore, the formative latent-variable model implies that an emotion model can be locally homogeneous or *locally heterogeneous*, with the latter implying variation (Table 1).

Indeed, evidence supports the idea that emotion models vary between individuals and across situations (e.g., De Leersnyder et al., in press; Kuppens & Tong, 2010; Kuppens et al., 2013; Kuppens et al., 2003). However, there are only a few studies comparing the variation of emotion models between and within individuals in one study (Kuppens et al., 2013). The formative latent-variable model would theoretically permit such a comparison. Thus, the formative latent-variable model accounts for the required property to allow variation of emotion models between and within persons.

The formative latent-variable model and the property of causal relationships between components. The formative latent-variable model can, but need not, include correlations between indicators. Hence, this allows causal relationships between indicators, beyond them determining the latent variable. This seems to fulfill the property of causal relationships between emotion components as posed by appraisal theories.

However, there is a caveat. Because the construct represents an integration of the indicators, one implication of the formative latent-variable model is that the correlations are *external* to the model (Table 2; Bollen & Lennox, 1991; Borsboom, 2008; Borsboom et al., 2003). For instance, anger is defined via arousal, aggressive thoughts, frowning, and motivation to attack. Correlations between these components are not important at all for the definition of anger. Therefore, the formative latent-variable model marginalizes the causal relationships between emotion components; statistically, they are treated as a nuisance (Schmittmann et al., 2013), in the sense that they are assumed to be determined outside of the model.

In contrast to this marginalization, theorizing and evidence in emotion research show that emotion components *do* have causal relationships that need to be explained. For instance, appraisals cause multiple different emotion components (for a review, see Scherer, 2009), and different emotion components are uniquely associated with each other without necessarily sharing a common cause (for a review, see Mauss & Robinson, 2009). In fact, as emotions cannot be understood or manipulated independently of their components (Moors, 2017), it is reasonable to hypothesize that the relationships between different emotion components constitute the emotion itself. As such relationships carry no importance in the formative latent-variable model, we conclude that it does not satisfactorily account for the property of an integrative psychometric model of emotions that requires causal relationships between emotion components to be pivotal.

Summary of the formative latent-variable model. Considering the evidence accumulated in emotion research, the formative latent-variable model cannot serve as an integrative psychometric model of emotions (Table 1). Although the formative latent-variable model accounts for the property of variation between and within persons as posed by constructionist theories, it cannot account for the other two properties required for an integrative psychometric model of emotions. First, it does not satisfactorily account for the property of identifying distinct emotions, as posed by affect-program theories. Specifically, it needs what are still unspecified external variables to identify the effects of exhaustive sets of components on the emotion, which may lead to interpretational confounding. Second, the formative latent-variable model does not satisfactorily account for the property of causal relationships between components, as posed by appraisal theories. Specifically, causal relationships between emotion components are possible yet uninformative for the measurement of the emotion.

In sum, the reflective and formative latent-variable models do not constitute integrative psychometric models of emotions. Despite their widespread use, their implications are largely not in line with evidence accumulated in research inspired by the three broad classes of emotion theories. Therefore, to integrate and advance emotion research, an alternative psychometric model is necessary. One such alternative, which has thus far not been directly applied to emotions, is the psychometric network model.

The psychometric network model

Many different systems can be represented as networks of connected components, from friendships between people to metabolic reactions and the Internet (Barabási, 2011). The network approach has also been introduced to psychometrics, referred to as the *psychometric network*

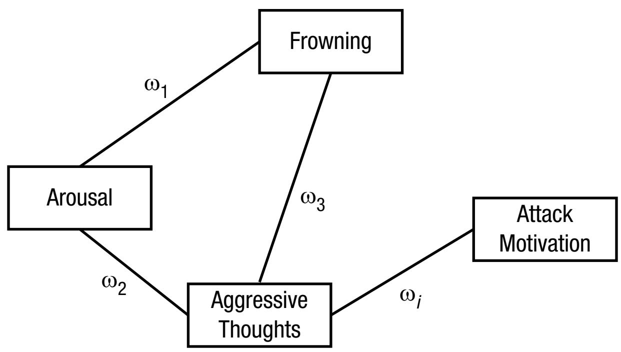

Fig. 3. Illustration of a network model of anger. Emotion components represent nodes. The connections of emotion components denote edges, representing conditional dependencies ω_i between emotion components controlling for all other components in the network. The entire network structure constitutes anger.

model. The central characteristic of the psychometric network model is that the indicators are conceptualized as having direct causal effects on each other (e.g., Borsboom, 2008). There is no unobservable (i.e., latent) construct that the indicators are measuring. Instead, indicators of a construct hang together because of mutual interactions between them. For emotions, this would imply that the network of causal relationships between emotion components represents the emotion. For instance, the relationships among arousal, aggressive thoughts, frowning, and motivation to attack would collectively constitute anger (see Fig. 3). In psychology, psychometric network models have recently been proposed as alternatives to latent variables models in research on intelligence (Van der Maas et al., 2006), psychopathology (Borsboom, 2017; Borsboom & Cramer, 2013; McNally, 2016), personality (Cramer et al., 2012), and attitudes (Dalege et al., 2016).

Formally, the psychometric network model entails two sets of elements, namely (a) *nodes*, representing indicators of a construct, and (b) *edges*, representing the relationships between nodes (Fig. 3). When we refer to the psychometric network model, we refer to the standard models applied in psychology to estimate psychometric networks, namely pairwise Markov random fields, in particular the Ising model for binary data (e.g., Epskamp, Maris, Waldorp, & Borsboom, 2018) and the Gaussian graphical model for continuous data (e.g., Epskamp, Waldorp, Mõttus, & Borsboom, 2018). In these models, two nodes are connected when they are conditionally dependent given all other nodes in the network. That is, if two nodes are related when controlling for all other nodes in the set, an edge ω_i connects them. Conversely, if two nodes are unrelated when controlling for all other nodes in the set, there is no edge connecting them.

There are two common estimation strategies to derive conditional dependence relationships from data (Epskamp & Fried, 2018; Van Borkulo et al., 2015). First, for both the Ising model and the Gaussian graphical model, edges can be estimated by regressions of each node on all other nodes in the set. Second, for the Gaussian graphical model, edges can be estimated as partial correlations. The partial correlations can be transformed to regression weights. Therefore, the first and second method lead to identical results. To avoid overfitting and obtain a sparse representation of the network, the edge weights are typically regularized, which is a statistical technique that shrinks the size of all edges and sets small edges to exactly zero. Tutorial articles explaining central steps of network analysis using the Ising model or the Gaussian graphical model are available (Costantini et al., 2015; Dalege, Borsboom, van Harreveld, & van der Maas, 2017; Epskamp, Borsboom, & Fried, 2018; Epskamp & Fried, 2018).

In a study following the logic of the psychometric network model, a researcher can assess the components of a specific emotion, just like for the latent-variable models. Afterward, the components are submitted to a network analysis to estimate their conditional dependencies. The entire network structure can then be visualized in various ways similar to Figure 3, for instance by algorithms producing the aesthetically most pleasing depiction. The question is, again, whether the psychometric network model accounts for the properties posed by the three broad classes of emotion theories.

The psychometric network model and the property of distinct emotions. The psychometric network model has an entirely different conceptualization of distinct emotions than both latent-variable models. In the psychometric network model, the nodes are not caused by a latent variable and do not predict a latent variable. In the psychometric network model, there is no latent variable at all. Instead, the relationships of an exhaustive set of indicators is the construct itself. Specifically, the network of mutual interactions forms a system—a mereological (i.e., part-whole) relationship between the indicators and the construct (Borsboom, 2008). That is, the network *constitutes* the emotion (for a description of constitution, see Craver & Bechtel, 2007). We argue that these systems can represent distinct emotions, thereby accounting for the property posed by affect-program theories (Table 1).

Our argument requires consideration of two points. First, what is the underlying network structure of an emotion? In this regard, research on emotion coherence shows that groups of components are more strongly connected with each other than they are with other groups of components (Hollenstein & Lanteigne, 2014).

For instance, there are stronger relationships between subjective feelings and cognitions as well as between motivations and expressions than there are across these components (e.g., Evers et al., 2014). Moreover, multiple elements within each component are also more strongly related than across components (Mauss & Robinson, 2009). For instance, the different motivations elicited by anger, such as motivation to attack, coercive intentions, or the long-term motivation to reconcile (Averill, 1983; Fischer & Roseman, 2007), are more tightly linked to each other than to facial expressions.

Such grouping of components maps onto concepts in network models. Specifically, multiple components of the same emotion may collectively form clusters (i.e., structures in which nodes that are connected to another node are themselves also connected) in a network (Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006). Nevertheless, it is reasonable to predict that multiple clusters of components of the same emotion do have some connections via shared components or via components that are related to multiple clusters. For instance, appraisals are linked to a multitude of components that may themselves belong to different clusters (e.g., Scherer, 2009). Together, these clusters could form tightly connected subgraphs in the network, which is called a *community* (e.g., Newman, 2004). Therefore, emotions might constitute networks in which strongly connected clusters are connected via short paths, forming a community.

Such a structure is called a *small-world network* (Watts & Strogatz, 1998; see also Milgram, 1967). This property applies to many networks (Boccaletti et al., 2006) because it is adaptive with respect to how information flows. In social networks, for instance, some persons who connect bigger groups of people can facilitate communication between these groups. In psychology, such structures were identified for attitudes (Dalege et al., 2016) and psychopathological disorders (Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011). Different elements of attitudes or different disorders are connected via bridge nodes in a small-world structure. Likewise, the community structure of emotions may form a small world. Thus, distinct emotions might be conceived of as communities with a small-world structure (see also Hsieh et al., 2011).

A second point related to modeling distinct emotions in the psychometric network model pertains to how the network structure (i.e., the small-world emotion network) may come to constitute an emotion. An answer to this question lies in the notion of *weak emergence* (e.g., Bedau, 1997, 2002; for an application to psychology, see Baumert et al., 2017; Costantini & Perugini, 2018). Weak emergence describes how systems that are formed of microstates can cause specific macrostates. In the version described by Bedau (2002), these macrostates are themselves autonomous and may have weak downward causal effects on the microstates. An example of weak emergence is a traffic jam. A traffic jam (i.e., a macrostate) is caused by the local interactions between individual cars (i.e., microstates). The emergence of the traffic jam, however, is not dependent on these specific cars. Other cars could have caused it, making traffic jams autonomous from the specific cars themselves. Moreover, once the traffic jam is formed, it slows down all the cars that initially caused it, thereby having a downward influence on them. This effect of the traffic jam on the cars is entirely determined by local interactions between the cars. The traffic jam does not develop causal powers independent of the cars. Therefore, the downward causal influence is called *weak*.

For emotions, this suggests that the causal relationships between emotion components can cause the weak emergence of an emotion. If associations in the small-world network structure increase, a stable system can emerge independently of which emotion component was activated first or whether multiple components were activated simultaneously (i.e., the emergent state is autonomous). These systems of interactions then force each emotion component into a specific state (i.e., weak downward causation). For instance, when a node in a network with only positive edges is activated, the other components are most likely also activated soon after. Note that this perspective is different from the notion of strong emergence, in which a construct independent from the components must be invoked. We instead argue that the causal network of emotion components constitutes the emotion.

The psychometric network model and the property of variation between and within persons. With respect to the property of variation between and within persons, the psychometric network model is similar to the formative latent-variable model. That is, the emotion components representing the network are grouped together on the basis of theorizing. Because there is no assumed common cause, models can be interpreted properly even if they vary between persons. Thus, the psychometric network model accounts for the property of variation between and within persons because it allows models to be homogeneous or heterogeneous (Table 1).

This is in line with evidence accumulated in emotion research. Specifically, research shows that emotions may be different between persons, groups, or cultures (e.g., Kuppens et al., 2013; Lindquist, 2013; Mesquita & Boiger, 2014). However, only a few studies have compared the models of different persons or of the same person across time. If the psychometric network model is estimated from cross-sectional data across persons, groups of persons with different network structures cannot be identified using current methods, but such techniques could of course be developed. For instance, specific methods have been developed to derive a person's idiosyncratic network model from time-series data (for an introduction to such methods, see Epskamp, Van Borkulo, et al., 2018; Epskamp, Waldorp, et al., 2018; Haslbeck & Waldorp, in press). Different networks could also be estimated for different groups of persons (e.g., different cultural groups), and their networks might be compared (Van Borkulo et al., 2017).

The psychometric network model and the property of causal relationships between components. The underlying idea behind the psychometric network model is that the system of causal relationships between nodes constitutes the respective construct (e.g., Borsboom & Cramer, 2013). Changes in one node directly reflect onto changes in other nodes. This makes the causal relationships the central feature of the psychometric network model. It therefore naturally accounts for the property of causal relationships between emotion components (Table 1).

However, as for all models, estimating causal effects is challenging. As edges in the psychometric network model are based on partial correlations or multiple regressions controlling for all other nodes in the set (i.e., conditional dependencies), they do not immediately represent causal relationships but are only indicative of causal structures (Epskamp & Fried, 2018; Epskamp, Waldorp, et al., 2018). Specifically, in the psychometric network model, two components are connected via an edge only when they are positively related controlling for all other components. Given that all variables of the network have been assessed, an edge between two components A and B is indicative of either a causal effect of A on B, a causal effect of B on A, bidirectional causal effects between A and B, or of a collider pattern ($A \rightarrow C \leftarrow B$, if A and B are initially uncorrelated). If A and B were initially correlated but are not connected via an edge in the network, this implies either the pattern of a mediation ($A \rightarrow C \rightarrow B$ or $B \rightarrow C \rightarrow A$) or of a common cause ($A \leftarrow C \rightarrow B$). Therefore, certain network structures correspond to different possible causal structures in estimated networks. Nevertheless, the central goal of the psychometric network model is to provide clues to the causal structure among components and, for instance, to assess which nodes are more likely to interact, because this is the theoretical perspective on which the psychometric network model is based.

Consequentially, a network model of emotions is in line with evidence that emotions evolve via a multitude of causal effects between emotion components (e.g., Lewis, 2005; Scherer, 2009). A possible example for anger is depicted in Figure 3. In this network, arousal, aggressive thoughts, frowning, and motivation to attack are connected. It is reasonable to predict that physiological arousal affects aggressive thoughts, mediating an effect on the motivation to attack (Zillmann, 1971). Given this mediation pattern, there is no edge connecting arousal and motivation to attack. Moreover, facial displays have social-communicative functions (Shariff & Tracy, 2011; Van Kleef, 2009). Thus, frowning, which could be caused by aggressive thoughts, may be used to communicate these thoughts to observers. Moreover, frowning may then feed back into arousal in line with research on facial feedback (Duclos et al., 1989). Similar models can be derived for other emotions.

Summary of the psychometric network model. The psychometric network model accounts for all required properties of emotions (Table 1). First, it accounts for the property of identifying distinct emotions as posed by affect-program theories. Specifically, in line with empirical evidence, distinct emotions might be conceptualized as small-world network structures that are weakly emergent. Second, the psychometric network model accounts for the property of variation between and within persons as posed by constructionist theories. Specifically, it allows models to be homogeneous or heterogeneous. Finally, the psychometric network model accounts for the property of allowing causal relationships between components as posed by appraisal theories. Specifically, the edges in a network are indicative of causal structures.

Discussion

Research on the nature of emotions is scattered across various emotion theories that are challenging or seemingly impossible to integrate (Barrett, 2006; Moors, 2017; Russell, 2015). We argued that identifying an integrative psychometric model for emotions may offer paths toward uniting emotion theories. After reviewing the three broad classes of theories about the nature of emotions, we proposed that any integrative psychometric model of emotions should account for at least three properties. In line with affect-program theories, such a model should allow distinct emotions. In line with constructionist theories, such a model should allow between- and within-person variation of emotions. And in line with appraisal theories, such a model should allow causal relationships between emotion components. Our review of relevant empirical evidence across domains of emotion research revealed, on the one hand, that the most frequently applied psychometric models, the reflective and formative latent-variable models, do not account for these properties. On the other hand, the psychometric network model does account for these properties. Specifically, the implications of the psychometric network model are in line with research on emotion coherence (e.g., Hollenstein & Lanteigne, 2014; Mauss & Robinson, 2009), the dynamics of emotions (e.g., Kuppens & Verduyn, 2017; Scherer, 2009), the cross-cultural and contextual dependence of emotions (e.g., De Leersnyder et al., in press; Mesquita & Boiger, 2014), and the multicomponential nature of emotions (e.g., Fischer & Roseman, 2007; Gausel et al., 2012). Thus, the evidence indicates that the psychometric network model can serve as an integrative psychometric model of emotions.

Like the psychometric network model we presented, some conceptualizations of emotions already proposed that emotion components dynamically interact (Lewis, 2005; Lewis & Liu, 2011; Sander et al., 2018; Thagard & Nerb, 2002). However, these approaches primarily focused on the neural level of analysis. Furthermore, these approaches were entirely theoretical and could therefore not be applied as psychometric models of emotions. Finally, emotions were assessed as part of networks in psychopathology research (e.g., Bringmann et al., 2016; Pe et al., 2015; Van de Leemput et al., 2014), attitudes (Dalege et al., 2016, 2017), aesthetics (Hosoya et al., 2017), and personality (e.g., Pavani, Le Vigouroux, Kop, Congard, & Dauvier, 2017), and mixed emotions were investigated with the help of co-occurrence networks of emotions (e.g., Moeller, Ivcevic, Brackett, & White, 2018). However, in these studies, emotions were treated as single variables and not conceptualized via the causal interaction of multiple emotion components as we propose. Applying the psychometric network model as described above has the potential to integrate insights from various emotion theories, to respond to calls to better capture the dynamics of emotion components, and to advance research on emotions in networks in other research domains.

If the psychometric network model can serve as an integrative psychometric model of emotions, then the seeming difficulties in reconciling affect-program theories, constructionist theories, and appraisal theories may disappear. The established properties of emotions have oftentimes been portrayed as being inconsistent with one another. For instance, that emotions are variable states has been portrayed as being inconsistent with the notion that emotions can be distinct or driven by appraisals (e.g., Barrett, 2006). It is conceivable that the broad emotion theories themselves are partly incompatible. However, this is not to say that the properties of emotions that these theories primarily explain (i.e., distinct emotions, variation between and within persons, causal relationships between components) are incompatible with one another. Therefore, a theory that can account for all of the properties is necessarily superior to three more specific theories that account for only one of the properties (e.g., Haig, 2005). Such a theory could facilitate progress toward a definition of emotions that is shared across different perspectives. According to the psychometric network model, such a definition requires that (a) emotions entail multiple components and (b) these components mutually influence each other, forming a network.

This leads to the question of which components should be considered as central and maybe even necessary for the definition of emotions. Across theories, emotions are theorized to entail subjective feelings, cognitions, action tendencies, expressive behaviors, and physiological changes. Within these broad classes of components, multiple concrete features can be identified (Fontaine et al., 2007). However, do all emotions require all components? Most likely not. Many emotions do not entail changes in some components but are nevertheless considered emotions. Because there is no unequivocal criterion with which to decide whether a certain state is an emotion or not, evidence suggests that emotions are like family resemblances (Fehr & Russell, 1984; Shaver et al., 1987). The more components the respective state has that are part of the general category of emotions, the more it is part of the family, and the more it resembles a typical emotion. Therefore, each emotion can be considered as a more or less central example of the broad category of emotions. Moreover, each instance of a specific emotion may not resemble another instance of the same emotion. Consequentially, each list of components that supposedly defines emotions in general or specific emotions in particular is necessarily only a prototype.

A related, so far unresolved question is how to operationalize the components of the psychometric network. A straightforward approach would be to include variables of the same assessment method. For instance, self-report items measuring all components of an emotion (e.g., for envy, see Lange et al., 2018) or selected items from comprehensive lists of component changes of emotions (Fontaine et al., 2007) could be used. Behind certain items, other network structures can hide. As an example, a self-report item assessing arousal may constitute a network of physiological reactions (see, e.g., Hsieh et al., 2011). Moreover, other items may reasonably be modeled as latent variables, combining psychometric network analysis and latent-variable modeling (Epskamp, Rhemtulla, & Borsboom, 2017). Which operationalization of components is most informative eventually depends on the research question. An interesting feature of this is that for all operationalizations, networks representing distinct emotions will most certainly share components with networks of other distinct emotions. The overlap could be analyzed for different operationalizations in future research to improve the understanding of relationships between emotions.

Beyond facilitating the integration of the three broad classes of emotion theories, a network model of emotions may also lead to new predictions. For instance, understanding emotions as networks of causally connected components has implications for the time course of emotions. When individual emotion components in a strongly connected network are activated in a specific situation, the causal feedback loops between components may quickly activate the entire network. As the connections are strong, the components continuously reactivate each other, sustaining the activity of the network. Thereby, the duration of the emotion is extended, and it becomes more difficult to switch back to a deactivated state. This difficulty of switching back to a deactivated state in strongly connected networks has been called *hysteresis* (for an illustration, see Cramer et al., 2016). In less strongly connected networks, hysteresis does not occur. Applied to emotions, the relation of network connectivity and hysteresis may provide a parsimonious account for why emotions vary greatly in their duration, which has so far been linked to numerous personal and contextual variables without a clear theoretical framework (for research on emotion duration, see Verduyn, Delaveau, Rotge, Fossati, & Van Mechelen, 2015). For instance, situations appraised as very relevant could strengthen the causal connections between emotion components, explaining why relevant situations increase emotion duration.

Even though we conclude that the psychometric network model will be useful for advancing emotion research and integrating theories in this area, it is important to keep in mind that it is just a model—a mathematical tool for analyzing data. Note that the reflective and formative latent-variable models are in no way different in this regard. As network analysis in emotion research will progress, detailed network theories of distinct emotions should be developed to allow confirmatory tests. As an example, such a theory derived from network principles has already been developed for attitudes (Dalege, Borsboom, van Harreveld, & Van Der Maas, 2019).

Furthermore, the psychometric network model may also lack integrative potential when it comes to specific theoretical claims. That is, the psychometric network model integrates the established properties of emotions, but it does not integrate all theoretical explanations provided for these properties in previous research. For example, even though we argued that the psychometric network model fulfills the property of distinct emotions as posed by affect-program theories, it cannot account for all theoretical viewpoints regarding the biological innateness of distinct emotions. The psychometric network model is consistent with the perspective that causal relationships between emotion components can be based on biologically innate mechanisms, such as the relationship between certain physiological changes and expressive behaviors. But the psychometric network model is inconsistent with the perspective that distinct brain modules activate all emotion components simultaneously with no causal effects among them. Thus, the psychometric network model shows promise in providing better theoretical integration but cannot integrate all theories about emotions at all levels.

Moreover, the psychometric network model also faces methodological challenges (for a similar discussion, see Fried & Cramer, 2017). This may lead to certain pitfalls when it comes to interpreting results and qualifying insights gained from network analysis. Specifically, the relationships of components estimated in the psychometric network model provide almost no information about the activation of each component, the heterogeneity in psychometric networks is difficult to quantify, different kinds of networks can provide different information, and psychometric network modeling is largely exploratory. We discuss each of these challenges in turn.

First, like all methods based on associations (just like the reflective and formative latent-variable models), the psychometric network model primarily provides information about relationships between variables (i.e., conditional dependencies) and not about to what extent variables are endorsed. The size of the edge weights is theoretically independent of the level of endorsement of the nodes. Moreover, it remains unknown whether two nodes are endorsed together by the same individuals. This limits the possibility to, for instance, determining whether one particular person experienced all components of an emotion network or of multiple emotion networks such that this person experienced a full-blown emotion or mixed emotional states, respectively (for an approach that shows mixed emotional states within persons and situations, see Moeller et al., 2018). As one exception, when estimating the Ising model from regularized logistic regressions, the analysis provides regression coefficients (i.e., edge weights) and intercepts. The intercepts can be interpreted as thresholds of nodes, that is, as the general level of activity in the network that is needed for the node to become active as well or, alternatively, the probability that the node is active given that other nodes are inactive (Van Borkulo et al., 2015). Still, the thresholds therefore do not directly estimate whether a node was active for each person or whether it was active for one person across situations. For networks estimated via the Gaussian graphical model, all variables are standardized, leading to intercepts of zero. This even precludes insights about the activation of components in the Gaussian graphical model.

Second, even though the psychometric network model allows variation between and within persons, it does not estimate this variation directly in typical applications. In cross-sectional networks of multiple participants in particular, for example, there could be (groups of) persons with different network structures. As is the case for all analyses based on relationships, it remains unknown whether the edges apply to any given person (Reitzle, 2013). It may well be that an edge connecting two emotion components results from responses of one group of persons and another edge results from responses of another group of persons. The cross-sectional emotion network estimated over these responses may then falsely suggest that both edges apply to all persons at the same time. However, this is true for all models considered in this article. Still, an advantage over the reflective latent-variable model is that variation between and within persons is theoretically allowed. Estimating variation requires complementing the psychometric network model with other methods. For instance, one strategy might be to estimate personalized networks (Epskamp, Van Borkulo, et al., 2018), that is, emotion networks for each person when analyzing data collected over multiple emotion-eliciting situations or when analyzing data from multiple assessments of all components in one emotion-eliciting situation. Clustering algorithms can be used to identify groups of persons with similar structures. Likewise, networks might even be estimated within persons for different situations, as a personalized network may also not apply to all situations that elicit the respective emotion in the person. Developing tools to estimate and address this variation should be a primary goal for future research (for potential approaches, see Fisher, Medaglia, & Jeronimus, 2018).

Third, even though cross-sectional and personalized emotion networks could be compared to gain a deeper understanding of variation in emotions, the comparison is not straightforward. This is because these networks provide different information (Epskamp, Waldorp, et al., 2018). A cross-sectional network estimated from assessments of component changes of multiple persons provides information about whether persons who tend to endorse one node also tend to endorse another node. For instance, persons who feel angry in one particular situation also tend to be more aggressive (e.g., Averill, 1983). Complementarily, multiple assessments of all nodes over time (e.g., multiple assessments of all components in one emotional situation) allow the estimation of two kinds of personalized networks. The so-called contemporaneous personalized network provides information about whether one particular person tends to endorse one node when this person also endorses another node. Like the cross-sectional network, when the person feels angry, this person is probably also more aggressive. The so-called temporal personalized network instead provides information about whether one node predicts another node at the next time point. Because feeling angry is associated with the motivation to reconcile in the long-term (Fischer & Roseman, 2007), it may be the case that when the person feels angry earlier, this will predict less aggression at a later time point. Thus, the cross-sectional network and contemporaneous personalized network may show a positive edge between feeling angry and aggression, yet the edge may be negative in the temporal personalized network. Determining how frequent such reversals are and what causes them are important tasks for future research. Which network is more relevant necessarily depends on the research question. It is possible to estimate contemporaneous and temporal networks for multiple persons individually and across all persons (Epskamp, Waldorp, et al., 2018). Moreover, methodological approaches provided by dynamic systems theory can facilitate the formulation of models in which fast and slow changes of different nodes are considered (for an example of a model of panic disorder, see Robinaugh et al., 2019).

Finally, the estimation of the psychometric network model as described here is largely exploratory. Specifically, no constraints are specified, and therefore no a priori hypotheses pertaining to specific edges are tested. When the psychometric network is estimated from assessments of multiple emotion components, the analysis will always provide a network that fits the data. However, application of the psychometric network model already does partly implement the underlying theory that the construct in question, such as the emotion, can be conceptualized as a network of causally interacting components. One should draw inferences from network analysis only if this theory applies. Despite the exploratory nature of the estimation strategies we discussed, the psychometric network model can be extended to allow confirmatory tests (e.g., Kan, Van der Maas, & Levine, 2019) that could be used to investigate future network theories of emotions.

Another possibility for future research could be to discuss other models in relation to emotions. For instance, multidimensional scaling (Hout, Papesh, & Goldinger, 2013) has been applied to test whether relationships between emotions (e.g., Russell, 1980) or relationships between components of emotions (Breugelmans & Poortinga, 2006) can be spatially arranged in a low-dimensional space. The spatial arrangement of emotions or emotion components in this low-dimensional space can be interpreted as a visualization of their similarities. Multidimensional scaling may therefore be used to visualize networks in an informative way by using the edge weights estimated during network analysis as its input (Jones, Mair, & McNally, 2018).

A last question relevant for emotion research may be how to use emotion networks as predictors or consequences of other variables. One reasonable strategy would be to include the other variables in the network. For instance, edges between emotion components and neuroticism could reflect that neuroticism is a predictor of emotion components or a consequence of them. How strongly neuroticism is related to components of one emotion could then also be compared to how strongly neuroticism is related to components of another emotion. Moreover, networks of different groups of participants can be compared as a means to determine the influence of another variable (Van Borkulo et al., 2017). For instance, networks of males and females could be compared with respect to their average edge weights. Beyond this, we also deem it possible that parameters derived from psychometric networks can serve as variables in another analysis. For instance, the overall connectivity of the network may predict characteristics of emotional processes, such as their time course, but could also be a consequence of external variables, such as the relevance of the situation. Future research may explore more strategies for taking other variables into account when conducting network analysis.

Conclusion

Emotion research has been characterized by strong theoretical advancement in different directions to a point at which theoretical integration has come to appear unattainable. We suggest that methodological advancement may foster progress on this end. Specifically, the psychometric network model provides a psychometric approach to emotions that may ultimately help to unite different emotion theories and contribute to clarifying what an emotion is.

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Note

1. For emotions, according to older appraisal theories, appraisal patterns may also be common causes of distinct emotions.

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