Emotional Processes of Foreign Language Learning Situated In Real-Time Teacher Support

de Ruiter, Naomi; Elahi Shirvan, Majid ; Talebzadeh, Nahid

Published in:
ECOLOGICAL PSYCHOLOGY

DOI:
10.1080/10407413.2018.1554368

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2019

Link to publication in University of Groningen/UMCG research database

Citation for published version (APA):

Copyright
Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment.

Take-down policy
If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): http://www.rug.nl/research/portal. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.
Emotional Processes of Foreign-Language Learning Situated in Real-Time Teacher Support

Naomi M. P. De Ruiter, Majid Elahi Shirvan & Nahid Talebzadeh


To link to this article: https://doi.org/10.1080/10407413.2018.1554368

Published online: 22 Jan 2019.

Submit your article to this journal

Article views: 197

View related articles

View Crossmark data

Citing articles: 1 View citing articles
**ABSTRACT**

The dynamic turn in the field of psychology of foreign-language learning has inspired researchers to capture the nitty-gritty dynamics of development in inter- or intraindividual variables. Despite the growing number of techniques for analyzing dynamics, there is still a need for techniques that capture how intraindividual dynamics are situated in a changing context. One of the techniques that can contribute to this knowledge is a clustering technique called Kohonen’s Self-Organizing Maps (SOM). In this study, we aimed to explore the intraindividual process of foreign-language enjoyment and foreign-language classroom anxiety in alignment with teachers’ level of emotional support during teacher-student interactions for two dyads. The findings indicated the emergence of recurring patterns of teacher support, and student anxiety and enjoyment. These patterns highlight the self-organizing nature of these teacher-student interactions, the bidirectional nature of this process, and, in general, the notion of teachers and students as dynamic systems. Moreover, the specific nature of the emergent patterns suggests that the traditional positive association between teacher support and student affect may (mostly, but not always) be generalized to real-time and real-life processes. And finally, our results point toward the importance of the student in determining the affective nature of the interactions from moment to moment.

**Introduction**

A positive teacher-student relationship plays a crucial role in the process of language learning within the ecology of the classroom (Byrnes, 2013), and emotions are an indispensable part of this process (Dewaele, 2015). For students, foreign-language enjoyment has been recently addressed as an important positive emotion (e.g., Boudreau, MacIntyre, & Dewaele, 2018; Dewaele & MacIntyre, 2014; Dewaele, Witney, Saito, & Dewaele, 2017; Dewaele, MacIntyre, Boudreau, & Dewaele, 2016; Elahi Shirvan & Talebzadeh, 2018a; Elahi Shirvan & Taherian, 2018). Enjoyment is pivotal in preventing foreign-language anxiety, which is the most negative emotion investigated in the field of applied linguistics (Dewaele, 2007; Horwitz, 2001; Horwitz, 2010; Gkonou, Daubney, & Dewaele, 2017; Lu & Liu, 2011; MacIntyre, 1999; Scovel, 1978). Together, students’ enjoyment and anxiety are thus two important emotions which should be emphasized when conducting research dealing with learners’ affect (Dewaele, MacIntyre, Boudreau, & Dewaele, 2016).
Recently, researchers have addressed the importance of contextual factors in the emergence of foreign-language enjoyment (e.g., Elahi Shirvan & Talebzadeh, 2018a, 2018b). More specifically, one of the key ecological factors contributing to the construction of positive and negative emotions in foreign-language learners’ performance is teachers’ emotional support (Hamre & Pianta, 2010; Pianta & Hamre, 2009). This includes teachers’ level of care, acceptance, trust, encouragement, and respect for students’ emotional well-being (Strati, Schmidt, & Maier, 2017). Indeed, teachers’ ability to construct socio-emotional connectedness and support as well as positive learning experience is pivotal (Arnold & Murphey, 2013; Gkonou & Mercer, 2017; Korthagen, Attema-Noordewier, & Zwart, 2014). A teacher’s emotional support can help learners with autonomy and comfort, and it is directly related to academic motivation and achievement (Feldlaufer, Midgley, & Eccles, 1988; Wentzel, 1998).

Despite the fact that research has indicated a positive association between students’ interest and teachers’ emotional support (Brewster & Bowen, 2004; Green, Rhodes, Hirsch, Suárez-Orozco, & Camic, 2008; Murray, 2009; Patrick, Ryan, & Kaplan, 2007; Sharkey, You, & Schnoeblen, 2008), research has hardly addressed the dynamics that characterize this relationship (Henry & Thorsen, 2018; Mercer, 2015; Mercer & Ryan, 2016). Such dynamics are important for gaining an in-depth understanding of the relationship between teacher emotional support and students’ emotions like enjoyment and anxiety, especially within classroom interactions. Students’ enjoyment and anxiety, and the teacher’s support, are likely not stable traits, but dynamic processes that interact and fluctuate across time (e.g., Gregersen, Macintyre, & Meza, 2014; Elahi Shirvan & Talebzadeh, 2017; Elahi Shirvan & Talebzadeh, 2018a). For instance, the relationship between affective variables and foreign language processes is likely nonlinear (Nowak & Vallacher, 1998), and their interconnections are likely emergent (Dewaele & Dewaele, 2017; Dewaele et al., 2017; Larsen-Freeman, 2016; MacIntyre & Legatto, 2011). This means that a teacher-student dyadic interaction will most likely not be characterized by one relationship (e.g., highly supportive teacher and highly engaged student), but that this relationship may take different forms across time, and that these different relationships will emerge from moment to moment.

Additionally, a teacher does not provide the same kind or amount of support to all learners. Instead, teachers provide different support for different learners (Hamre & Pianta, 2005; Merritt, Wanless, Rimm-Kaufman, Cameron, & Peugh, 2012; Pakarinen et al., 2014; Rudasill, Gallagher, & White, 2010). Therefore, it is important to also study interindividual variability with regard to teachers’ support.

Finally, recent research regards teacher support as multidimensional (Anderman, Andrzejewski, & Allen, 2011) and malleable (Gehlbach, Brinkworth, & Harris, 2012), one major aspect of which is emotional (Federici & Skaalvik, 2014; Semmer, Elfering, Jacobsen, Perrot, Beehr, & Boos, 2008). Research to date, however, tends to investigate teacher support as a unidimensional construct that does not change in quality over time.

The current study

Inspired by Mercer (2015), who invites researchers to apply “more explicitly relational perspectives” (p. 81), we aimed to achieve deep insights into the dynamic relationship
between students’ experiences of anxiety and enjoyment during second-language learning under the contextual factor of their teachers’ changing emotional support. In this study, we go further than conceptualizing the teacher’s support as an independent variable that has influence on the learner’s experience. As Steenbeek and van Geert (2013) suggest, students and teachers might be best conceptualized as a dynamic system, as there is continuous and reciprocal influence between the two. From this perspective, teacher and student are the main components of this dyadic system, both of whom consist of their own emotional, behavioral, and cognitive components. As discussed above, for foreign-language learners, emphasis has recently been put on both enjoyment and anxiety (Dewaele & Dewaele, 2017; Dewaele & Alfawzan, 2018; Elahi Shirvan & Taherian, 2018), and on teacher support (Arnold & Murphey, 2013; Gkonou & Mercer, 2017; Korthagen et al., 2014).

We examine the nature of these student-teacher systems in the specific context of questions from the teacher. This context is useful, as it creates the kind of student-teacher interaction that is relevant for our aim. First, it is challenging for students to effectively communicate emotions during second-language interactions (Fredrickson, 2013). As such, emotionally laden questions posed by the teacher provide “communicative pressure” (Gass, 2003, p. 224). Such pressure is important, as “learners need to be pushed to make use of their resources; they need to have their linguistic abilities stretched to their fullest; they need to reflect on their output and consider ways of modifying it to enhance comprehensibility, appropriateness, and accuracy” (Swain, 1993, pp. 160–161). Second, due to the challenging nature of personal questions posed by the teacher, the teacher—in return—is invited to change his/her level of support throughout the interaction in order to relieve possible stress elicited by the context, while maintaining a certain level of pressure necessary for the student to be challenged linguistically. This will likely result in a constant flux between high and low support. Finally, given the teacher’s adaptive support of the student, the personal nature of the questions allows the student to express interest during these second-language interactions. This specific context therefore allows us to gain a rich picture of the nature of fluctuating student affect and teacher support, and the changing interactions between these processes.

From a methodological perspective, studying foreign-language classroom anxiety and enjoyment has been mainly conducted with a quantitative etic lens (e.g., Dewaele, Petrides, & Furnham, 2008; Elkhafaifi, 2005; Gardner & MacIntyre, 1993; Horwitz, Horwitz & Cope 1986; Horwitz, 1986; MacIntyre & Gardner, 1989; Price, 1991; Matsuda & Gobel, 2004; Saito & Samimi, 1996; Scovel, 1978; Young, 1991), which follows traditional group-based and aggregative approaches aimed at generalization to the population; i.e., nomothetic research (Larsen-Freeman, 2015). Alternatively, with the recent dynamic turn in the field, it has become increasingly important to assess the within-individual (or in this case, the within-dyadic) relationship between teachers’ and students’ emotions in situ (i.e., as they occur) in order to gain an understanding of the dynamics and complexities that underlie this relationship. Despite the importance of emotions in second-language learning, little is known about how teachers’ and students’ emotions and support relate from moment to moment in relevant contexts.

In order to study the moment-to-moment changes of teacher-student systems in situ, suitable analytical tools are needed. Several methods within the realm of psychology of
language learning are being developed for this purpose. Most of these new methods focus on how change within a univariate time series is embedded in time. For example, the idiodynamic method (i.e., self-ratings of changes in constructs like emotions; MacIntyre & Legatto, 2011) allows researchers to study moment-to-moment changes of univariate time series, and the retrodictive qualitative method (Dörnyei, 2014) identifies end states and works backward to assess how developmental trajectories lead to certain outcomes (Chan, Dörnyei, & Henry, 2015; Dörnyei, 2014). These methods are highly useful for studying developmental trends or variability of a single construct. However, since a system consists of various interacting components, there is a need for methods that examine the relationship between these components, and how they evolve over time. In other words, we need a methodological tool which captures fluctuations in multivariate data.

Therefore, despite the methodological advancements implemented in recent research, the field is still in need of tools for capturing the nitty-gritty moments of change of an entire system during interactions, and these remain uncommon (Ram & Gerstorf, 2009; Van Geert & Van Dijk, 2002). Ideally, such methods should be able to capture the “self-organizing capacity” of the dynamic system under study. Self-organization refers to the process in which order emerges from the interaction of the components of a system without direction from external factors and without a plan for that order (Dörnyei, 2014). Within the field of psychology, De Ruiter, Van Der Steen, Den Hartigh, and Van Geert (2017) have recently used Kohonen’s Self-Organizing Maps (SOM; Kohonen, 1982) to capture this self-organization of order in individuals embedded in a social context.

Kohonen’s Self-Organizing Maps has been more commonly applied in areas such as computer learning (Kohonen, Schroeder, & Huang, 2001), chemistry (Marco, Ortega, Pardo, & Samitier, 1998; Nielsen, & Yezierski, 2015), ecology (Lek & Guegan, 1999), engineering (Frey 2012; Kohonen, Oja, Simula, Visa, & Kangas, 1996; Panapakidis, Papadopoulos, Christoforidis, & Papagiannis, 2014), and biology (Tamayo et al., 1999). De Ruiter, Van Der Steen, et al. (2017) demonstrated how this method can be used in psychology by providing a case study involving emotional and behavioral self-experiences of an adolescent during a real-life interaction with his parent. Their results showed how the components of the adolescent system (i.e., self-affect and autonomy) are dynamic, such that the relationship between these intraindividual components is always changing. The authors then also showed how the adolescent’s self-experiences are related to external dynamics, namely the parent’s behavior. This method can be readily applied in the domain of foreign-language learning to explore intraindividual variability of key components in foreign-language learners’ learning process, and how these components are embedded within the changes in teacher support. Thus, we use SOM to investigate the continuous interactions between the student’s two core emotions during second-language learning (enjoyment and anxiety) and the teacher’s emotional support.

Using the SOM has a number of advantages over other methods more commonly used in psychology. First of all, other time-series techniques enable the researcher to either investigate intraindividual change across time (e.g., Ram & Gerstorf, 2009; Tan, Shiyko, Li, Li, & Dierker, 2012) or examine the association between intraindividual fluctuation and environmental variables (e.g., Shiyko & Ram, 2011), but SOM contributes to the simultaneous study of these two features. Thus, “SOM offers opportunities
for studying intra-individual variability of multiple components embedded in a constantly changing context” (De Ruiter, Van Der Steen, et al., 2017, p. 612). The SOM allows for the study of embeddedness in a context in a unique way. Rather than determining statistical similarities between variables or cases, as in hierarchical agglomerative clustering (Borgen & Barnett, 1987), for example, the SOM identifies the dynamic correspondence between variables (Skific & Francis, 2012).

Second, most methods are used for confirmatory analyses, where specific predefined relationships are tested. The SOM, in contrast, is a data-driven technique that can be used for exploratory and inductive analysis (Ultsch & Vetter, 1994). As our aim is broad and explorative, namely to understand the nature of student-teacher systems during second-language lessons, this technique is the most suitable.

**How does the SOM work?**

SOM is an artificial neural network that enables us to explore patterns (or “clusters”) of variables as they change across time. In SOM, the vectors are organized in two layers, an input layer and an output layer. The output layer becomes the “map,” which is built using the input. The output vector (related to the developing map) updates itself with every addition to the input vector (i.e., each new datum), such that dissimilarity between the input and output vectors is reduced with each new iteration. During this process, similar sets of data are placed close to one another (Kohonen, Schroeder, & Huang, 2001). This process continues until the output vector can fully represent the data organization through a “map” that is characterized by clusters (Kohonen, 1982; Lagus, Honkela, Kaski, & Kohonen, 1996). In doing so, the SOM technique maps unknown structure in the time-serial data in a recursive process and portrays the emergence of this structure as output. This process is illustrated in Figure 1. These clusters can be represented as a new higher-order time series (of transitions between clusters across time), which can be used for subsequent analysis. For more information regarding the underlying algorithm of SOM, see Kohonen (1982).

Requirements of the SOM

For the use of SOM, multiple time-serial variables are required, which are measured with equal intervals and across the same time span (De Ruiter, Van Der Steen, et al., 2017). Time-serial input for SOM can be continuous or discrete. All variables for each data point need a value. This can be done in two ways: measuring the variables with the same time interval or applying a smoothing technique that can be used to fill gaps in time series (Fu, Chung, Ng & Luk, 2001). In our present data, time series have equal time intervals, thereby making smoothing unnecessary. Finally, in order to prevent the artificial dominance of any given variable in the clustering process, all the variables should have the same scale, and if not, should be normalized (Taner, 1997).

Different statistical software packages can be used to conduct SOM, such as Tanagra (Rakotomalala, 2003), Matlab (Vesanto, Himberg, Alhoniemi, & Parhankangas, 2000), R (Wehrens & Buydens, 2007), and Orange (Demšar et al., 2013). In this study, we used the Tanagra software program.

Method

Participants

For the purpose of this study, we used observational data of two student-teacher dyads. The teacher, who was the university professor of the course Listening and Speaking in English, was video recorded during a conversation with four students. Two of these students were selected for further investigation (resulting in two sets of dyadic data, with each student interacting separately with the teacher). These two students were selected based on the fact that they most clearly expressed their anxiety and enjoyment in their facial expressions and body language, as well as nonverbal communication. The two students were 18-year-old female freshman students majoring in English language at the University of Bojnord, Iran.

Procedure

The conversations between the teacher and the students were video recorded. These involved three questions: (1) Describe a place that you like, (2) What kind of noises annoy you? and (3) What makes you feel stressed? The teacher asked follow-up questions for each question. The topics had been piloted with three students, during which we found that students were comfortable giving responses to the teacher with regard to these topics, thus allowing us to recognize the teacher’s emotional support more clearly (Kikas & Mägi, 2017). The conversations lasted approximately eight minutes.

Data analysis

Coding

Anxiety and enjoyment in the learner and the teacher’s emotional support were coded based on their verbal and nonverbal communicational cues, and where thus event based.
Each variable was given a score from 1 to 3 (i.e., 1: low anxiety, 2: medium anxiety, 3: high anxiety). Table 1 shows the coding for each variable. The second and the third researcher of this study coded the data. These two researchers developed the coding criteria and reached 90% agreement over the coding of the collected data. The three variables demonstrated a high level of interrater reliability between researchers (from $K = .85$ to $K = .95$).

**Kohonen’s Self-Organizing Maps**

When using SOM, it is advised to use the smallest number of clusters possible, as this provides the clearest picture of the multivariate data, and to use no more clusters than variables in the dataset (Ultsch, 1999). As we have three variables, the SOM was done for two clusters (i.e., the minimum number of clusters) and three clusters (i.e., the maximum number of clusters). We then assessed which number (two or three) best fit the data, based on the following information.

In accordance with De Ruiter et al.’s recommendations, we examined (1) whether clusters consisted of relatively equal amounts of data (in order to ensure that there are no redundant clusters that consist of a small amount of data, relatively speaking). This can be seen in the percentages in Table 2 and 3. Next, we assessed (2) whether each variable contributes significantly enough to the clusters. The contribution of a variable can be described as the “weight” of that variable in the cluster. This is characterized by test values (TVs, see Table 2 and 3). TVs are calculated by comparing the mean of a variable on the whole dataset to the mean of that variable in a given cluster (this was conducted in Tanagra). TVs greater than two indicate a significant effect ($p < .05$), indicating that the variable has sufficient weight in a given cluster (Rakotomalala, 2003).

After considering the above two points, we then assessed whether a two- or three-cluster “map” (i.e., cluster set) explained the most Total Sum of Squares (TSS). A higher explained ratio of TSS indicates a better-quality map. These considerations are described

### Table 1. Verbal and nonverbal codes of the three variables in the study.

<table>
<thead>
<tr>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Teacher emotional support</strong></td>
<td>No facial expression</td>
<td>Nodding the head</td>
</tr>
<tr>
<td></td>
<td>No head or body movement</td>
<td>No verbal feedback</td>
</tr>
<tr>
<td></td>
<td>No verbal or nonverbal feedback</td>
<td>Using gap fillers such as <em>hmmm</em></td>
</tr>
<tr>
<td><strong>Student enjoyment</strong></td>
<td>Leaning</td>
<td>Smile</td>
</tr>
<tr>
<td></td>
<td>Hands on the chin</td>
<td>Forward leans</td>
</tr>
<tr>
<td></td>
<td>Straight gaze</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Low eye contact</td>
<td></td>
</tr>
<tr>
<td><strong>Student anxiety</strong></td>
<td>Slight forward lean toward the teacher</td>
<td>Backward lean,</td>
</tr>
<tr>
<td></td>
<td>Natural</td>
<td>Back against chair</td>
</tr>
<tr>
<td></td>
<td>Spontaneous</td>
<td>Sitting upright</td>
</tr>
<tr>
<td></td>
<td>Natural head nodding</td>
<td>Generally closed body position</td>
</tr>
</tbody>
</table>

ECOLOGICAL PSYCHOLOGY 133
below, for the two cases separately. Finally, SOM provides information about the temporal transitions between clusters for each dataset in the form of a new higher-order time series (see Figures 2 to 4). To ensure that the SOM is detecting meaningful patterns in the time series, rather than patterns based on random noise, we visually examined the nature of these temporal transitions. This was done for the original time series and for the shuffled versions of those time series. We conducted the SOM analysis for both versions of the data. If the SOM analysis provides highly scattered cluster transitions across time (with no visible structure) when the shuffled data is used, and relatively large chunks of clusters (with visible structure) when the original time series are used, this suggests that the original time series do not resemble a time series without any underlying temporal structure. Figure 2 portrays the transitions between clusters based on the original time series for one dyad (A) and based on the shuffled data for the same dyad (B). The figure shows that the transitions between clusters are much more structured (i.e., a cluster is active for larger blocks of time) for the original data (A), and that this differs from the kind of transitions seen for the shuffled data (B), where transitions between clusters are not structured at all (i.e., for each second a new cluster is active). Based on our visual comparison of the two, we are confident that the resulting maps in our analysis represent meaningful patterns.

### Results

#### Dyad 1

The findings for the first dyad show that a map consisting of two clusters was the best fit for the data (see Table 2 for cluster characteristics). Firstly, two clusters explained a satisfactory ratio of TSS (0.51) and resulted in a relatively equal distribution of data across the clusters. Moreover, the TVs show that each cluster is represented by variables

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Cluster 1 (51.7%)</th>
<th>Cluster 2 (48.3%)</th>
<th>Cluster 3 (36.6%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TV</td>
<td>Cluster mean (SD)</td>
<td>Overall mean (SD)</td>
<td>Cluster mean (SD)</td>
</tr>
<tr>
<td>Teacher emotional support</td>
<td>4.27 (0.83)</td>
<td>2.07 (0.86)</td>
<td>-4.27 (0.86)</td>
</tr>
<tr>
<td>Student enjoyment</td>
<td>19.05 (0.60)</td>
<td>1.84 (0.88)</td>
<td>-19.05 (0.26)</td>
</tr>
<tr>
<td>Student anxiety</td>
<td>-20.49 (0.30)</td>
<td>1.92 (0.93)</td>
<td>20.49 (0.46)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Cluster 1 (36.6%)</th>
<th>Cluster 2 (31.8%)</th>
<th>Cluster 3 (31.5%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>TV</td>
<td>Cluster mean (SD)</td>
<td>Overall mean (SD)</td>
</tr>
<tr>
<td>Teacher emotional support</td>
<td>-14.6 (0.21)</td>
<td>2.03 (0.96)</td>
<td>3.17 (0.91)</td>
</tr>
<tr>
<td>Student enjoyment</td>
<td>-5.99 (0.50)</td>
<td>1.77 (0.73)</td>
<td>13.95 (0.50)</td>
</tr>
<tr>
<td>Student anxiety</td>
<td>1.17 (0.89)</td>
<td>1.76 (0.91)</td>
<td>-10.73 (0.00)</td>
</tr>
</tbody>
</table>
that have significant weight: The test values (TV) were all significant (i.e., TV > 2 is statistically significant). This information can be found in Table 2 below. In contrast, while a map consisting of three clusters resulted in higher explained ratio of TSS (0.60), the third cluster was underrepresented in the data (with only 16.1% of data falling in this cluster). Moreover, the characteristics of the third cluster were similar to those in Cluster 1 from the two-cluster map, therefore making the third cluster redundant.

**Figure 2.** A timeseries of the temporal order of clusters based on the SOM cluster output. The time series are based on the original data for one dyad (A) and for the shuffled data of the same dyad (B). Time is shown on the x-axis and the activation of the two clusters is shown on the y-axis. Fluctuations between clusters show clear structure in Figure 2A and not in Figure 2B.

**Figure 3.** Temporal emergence of Cluster 1 and Cluster 2 for Dyad 1. Note that this is the same data portrayed in Figure 2A, but without the line connecting transitions between Cluster1 and Cluster 2, such that the duration and timing of cluster activation is emphasized here rather than the nature of the transitions between the two.
Based on this, we concluded that a 2-cluster option offers the best fit to the data for the first dyad.

**Cluster characteristics**

Based on the absolute values of test values (Table 2), we can see that the students’ emotions have more weight in Dyad 1’s map compared to the teacher’s support (while the teacher’s support has a significant contribution to the clusters based on the absolute TV, the absolute TVs for the student’s affect are relatively higher). This suggests that, for Dyad 1, the student may be a more influential component in the teacher-student system.

Cluster 1 is clearly the “positive” cluster, where the teacher’s support is positive, student’s enjoyment is positive, and student’s anxiety is negative. Cluster 2 is a more “negative” cluster, with opposite characterization (see TVs in Table 2). Together, the clusters for Dyad 1 provide a teacher-student profile that resembles a “linear” relationship between teacher support and student’s emotions: positive teacher support corresponds with more positive student affect, while negative teacher support corresponds with more negative student affect.

Figure 3 shows the temporal transitions between the two clusters for Dyad 1: both clusters are present throughout the interaction, but it seems as though the “negative” cluster (Cluster 2) is more present in the first half of the conversation than the second half, whereas the “positive” cluster (Cluster 1) is more present later in the interaction as compared to the beginning. This indicates that the interaction may have become more positive as it unfolded.

**Dyad 2**

For the second dyad, three clusters provided a better fit with the data than two clusters. Three clusters resulted in a sufficient level of explained TSS (0.54) and a good distribution of data points across the three clusters (see percentages in Table 3). Moreover, each cluster was represented by variables with significant weight (see TVs in Table 3), with the exception of student anxiety in Cluster 1. In contrast, a two-cluster option
resulted in a significant drop in the explained ratio of TSS (0.36), deeming this configuration as unsatisfactory.

Cluster characteristics

In contrast with Dyad 1, Dyad 2 is characterized by clusters that vary in the relative weight of teacher versus student. Whereas the student had more weight in both clusters for Dyad 1, for Dyad 2 the student has more weight in one cluster (Cluster 2) and the teacher has more weight in the other two (Cluster 1 and 3). This suggests that the relative influence of the teacher or student in this teacher-student system may depend on the specific interaction pattern that they are currently in.

Unlike Dyad 1, the association between teacher support and student affect is not consistently “linear” for Dyad 2. Cluster 1 and Cluster 2 can be characterized as having a linear relationship: Cluster 1 seems to be a “negative” cluster, where the student’s negativity stems primarily from a lack of enjoyment (as there is no significant weight from the anxiety component), and Cluster 2 can be characterized as a “positive” cluster. In contrast, Cluster 3 is an “opposing” cluster at the dyadic level, where positive teacher support occurs together with high student anxiety and low student enjoyment. Therefore, the valence of teacher support does not correspond with the valence of student affect in this cluster.

Aside from the presence of an “opposing” cluster at the dyadic level, Dyad 2 also differs from Dyad 1 in terms of the weight of the student in determining the quality of the interaction patterns. Whereas the student had more weight in both clusters for Dyad 1, this is only the case for one out of the three clusters for Dyad 2 (i.e., in the “positive” cluster, based on their absolute TV values).

Figure 4 shows the temporal ordering of Clusters 1, 2, and 3 for Dyad 2. Throughout the entire conversation, the ‘positive’ cluster (Cluster 2) is more present in the later sections of the interaction. As Cluster 2 is the only cluster in which the student is positive (i.e., the teacher is also positive in Cluster 3), this suggests that the student (much like the student in Dyad 1) may have transitioned from being negative to being slightly more positive throughout the conversation, and that a similar transition is not clearly visible for the teacher. This may suggest that the slight increase in student enjoyment across time was not due to the teacher.

Case study conclusions

These results illustrate that teacher support, and student enjoyment and anxiety, fluctuate throughout the interaction, as components of the dyadic system. Together, the affective components of the teacher and student iteratively interacted, such that patterns emerged across the interaction. For both dyads, each interaction pattern repeatedly occurred across the interaction, demonstrating that they have “attractor” qualities. Moreover, for both dyads, transitions were made between contrasting interaction patterns (i.e., positive and negative affective patterns). With regard to the content of the clusters, both dyads seemed to demonstrate a transition across the interaction, such that the more “positive” clusters became more dominant as the interaction progressed.
While the dyads share these global characteristics, the Self-Organizing Maps technique allowed us to reveal dyadic idiosyncrasies with regards to the make-up of their interaction patterns. First, whereas Dyad 1 was characterized by a “linear” relationship between teacher support and student affect, Dyad 2 only partially was (such that one of the two clusters was characterized by positive teacher support but negative student affect). Second, whereas the student had more weight in both of the clusters for Dyad 1, this was only the case for one of the three clusters for Dyad 2.

**Discussion**

Our results highlight the value of assessing the nitty-gritty dynamics of dyadic interactions. Using the Self-Organizing Maps technique, we were able to reveal clear dyadic differences with regard to content of affective patterns of interaction, as well as whether (and when) the teachers’ or students’ emotions were more influential in determining the quality of the interaction. While the case-study nature of these analyses does not allow for any conclusions regarding why these dyadic differences occurred, or what they may be important for, we hope to have illustrated the kind of unique information that can be gained using this approach, such that future studies can further explore such dyadic differences.

Crucially, aside from the differences between the dyads, our results also illustrate key similarities between the dyads, which may be useful for theory formation and further research. For instance, in terms of similarities in the quality of patterns themselves, the fact that most of the interaction patterns were “linear” in the relationship between teacher support and student affect, suggests that extant group-based studies suggesting a positive association between teacher support and student enjoyment/anxiety (Brewster & Bowen, 2004; Green et al., 2008; Murray, 2009; Patrick, Ryan & Kaplan, 2007; Sharkey, You & Schnoebelen, 2008) might indeed generalize to individual and real-time processes. This is a growing concern in the social sciences, where the importance of examining whether results from nomothetic research can be generalized to individuals is being stressed (Fisher, Medaglia, & Jeronimus, 2018; Van Geert, 2014; Molenaar, 2004). Importantly, the fact that this positive association was not observed for all moments in the interaction (i.e., not for Cluster 3 from Dyad 2) suggests that this group-level association may not fully describe individual and real-time processes. Common group findings regarding the association between teacher support and student affect may be only partially generalizable to the individual level.

Moreover, the abovementioned positive relationship between teacher support and student affect is often discussed in terms of teachers having the primary role (Claessens et al., 2016; Korthagen et al., 2014). Our results may bring the pivotal role of the teacher into question. In our case study, the student often had more weight than the teacher (all of the time of Dyad 1, and some of the time for Dyad 2). Moreover, the transition toward more positivity observed in the student from Dyad 2 could not be clearly attributed to a change in the teacher’s support. Our results therefore generate a new hypothesis that can be tested in future research.

Next, both dyads showed a temporal pattern of clusters that suggested that the dyads became more positive as the interaction progressed. Whereas, Fredrickson (2013)
describes how micro-moments of positive air occur, during which one individual becomes invested in another one, our results suggest that these “positive” moments were more than just sporadic moments. Increased moments of positivity resembled interpersonal patterns that clearly emerged across the interaction and become increasingly dominant throughout the interaction. This is more in line with the idea that these positive moments pave the way for an emergent sense of rapport (Vacharkulksemsuk & Fredrickson, 2012).

Regarding the interpretation of these findings, it is worth mentioning that the in-depth understanding of the two case studies can only provide a generalization from empirical data to theory (including meta-theories and specific theories; Flyvbjerg, 2006; Ruddin, 2006) rather than a generalization from empirical measurement to a population description (Lee & Baskerville, 2003). The specific nature of the emerging patterns of learners’ enjoyment and anxiety and teacher’s support should not be generalized to all the dyadic interactions in second-language lessons. Indeed, our findings support the idea that these interactions are idiosyncratic, and should be treated as such.

The value of our findings lies predominantly in illustrating and supporting the principles of the metatheory of complex dynamic systems (De Bot, Lowie, & Verspoor, 2007; Thelen & Smith, 1994; Van Geert, 1994), and provide support for the notion of self-organization of teacher-student interactions as dynamic systems.

Specifically, our results suggest that order emerges from the iterative interactions between student affect (enjoyment and anxiety) and the teacher’s emotional support. This iterative development is captured in this case study through the very nature of Kohonen’s Self-Organizing Maps analysis, where the scores for anxiety, enjoyment, and support iteratively emerged into a set of recurring patterns.

Importantly, none of these patterns were static once they emerged. They dynamically occurred, demonstrating transitions amongst themselves, and therefore, constant change. Our results thus support the notion of teacher-student affective systems as being characterized by both stability and variability. Stability refers to the recurring patterns that have self-organized, and variability refers to the subsequent transitioning between these emergent patterns as time progresses (Van Geert, 1994). This resembles the notion of an attractor landscape, which is a malleable collection of a system’s attractor states, where the system moves from one attractor state (i.e., pattern) to another across time (De Ruiter, van Geert, & Kunnen, 2017).

As such, our results support the notion that teachers and students, and the teacher-student dyads that they form, may not accurately be characterized by stable descriptors such as “supportive” teachers, or “interested” students. Instead, dyads—such as those in our study—may develop a positive pattern (teacher support and positive student affect) that juxtaposes a negative pattern (negative teacher support and negative student affect). Dyads may therefore develop various interaction patterns that can differ greatly from each other in quality. Each pattern, moreover, can most likely not be reduced to the personal teacher and student characteristics, in the sense that the dyadic patterns are the sum of the characteristics of the individuals. Instead, the relational identities are co-constructed in the interaction (Tracy & Robles, 2013). As teachers and students interact, both will endure a coadaptation process in which they influence each other’s responses—at the cognitive, emotional, motivational, and behavioral levels (Korthagen...
et al., 2014). For instance, in one of the many moments of positive association between support and affect in Dyad 2, the teacher asked the student about annoying noises and how much they bother her via a facial expression of uneasiness when asking about cars and street noises. This represents the teacher’s related identity to these particular sounds. This facial expression was mimicked by the student, leading to the same facial expression and the emotion behind it by the student. This is known as emotional contagion (Hatfield, Cacioppo, & Rapson, 1993). The real-time nature of this data therefore illustrates emotional contagion at work, which may be an important characteristic of how teachers and student co-construct their affective patterns in real-time interactions.

The co-construction of specific teacher-student affective patterns is thus a key conceptualization that is supported by the current study. With it, another important characteristic of teacher-student interactions is highlighted by our case study: the student is likely not a passive receiver of feedback, but is instead an active agent. A student’s own iterative processes not only contribute to how the interaction will proceed, but also enable or prevent the reception of any given feedback (Larsen-Freeman, 2015).

Conclusion

Language learning occurs at the microlevel of social activity, involving interpersonal interactions with the teacher (The Douglas Fir Group, 2016). In order to reach a micro-level understanding of a teacher’s emotional support and its relationship with language learners’ anxiety and enjoyment, we used a well-adapted technique, Kohonen’s Self-Organizing Maps (1982), for the analysis of conversations between a teacher and two learners. This technique allowed for a rich account of the teacher-student affective system as a real-time process. While existing methods may give insight into the static or longitudinal relationship between teacher support and student affect, the SOM provided unique insight into the moment-to-moment relationship between these processes for the first time. In doing so, it highlighted and illustrated the conceptualization of teachers and students as components of a system, where—together—they develop (potentially contrasting) ways of interacting that emerge iteratively across time.

References


