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New perspectives on computer-mediated communication research: A social network analysis approach

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Introduction

Computer-mediated communication (CMC) is an online text-based interactive process that has increasingly become part of our personal and professional lives over the past three decades. The study of CMC is a topic of interest that heavily relies on a range of data-driven tools and methods to analyse and visualise digital discourse (Bou-Franch & Blitvich, 2018; Zourou, 2019). Meta-analyses on CMC in education (Domahidi, 2018; Liu *et al.*, 2018) have shown, however, that the ways in which language and interaction are analysed within online spaces vary tremendously across studies and "preclude an unequivocal answer to the question of the effectiveness of computer-mediated communication" (Lin, 2015, p. 86). The efforts that have been made often take established theories of mediated communication and aim to translate them to the new realm of digital discourse, but they often fail to recognise the affordances of the digital context, the wealth of user data that is available and the impact this context has on human interaction (Carr, 2020; Jacobs & Tschötschel, 2019).

It is imperative that we improve our understanding of CMC, particularly in a CALL context, by formulating and testing new, replicable methods for analysis, and use this knowledge to integrate and evaluate CMC spaces in education. In this chapter, the ways in which CMC has been analysed over the years will be elaborated upon. Next, new insights into CMC text analytics will be presented, using examples from a peer

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interaction project in which foreign language learners (N = 188) at a private university in Japan collaborated on a number of learning tasks through Google Classroom (Peeters & Mynard, 2019, 2021). The main goal of this chapter is to show how educators and researchers can start to identify structures of interactional rules, procedures and conventions that govern CMC. This way we can improve our understanding of how language students interact when they are part of an online community for learning, how they form bonds with others and how they exercise their agency within an online space (Peeters, 2020).

This chapter further emphasises the role of CMC text analytics in the context of Smart CALL. This context embodies a number of distinct features that revolve around 1) the ways technologies and learning environments can be designed and modified to suit the individual language learner, 2) the ways these technologies and learning environments can be adjusted to fit the context in which that learner is working, and 3) the ways in which they allow meaningful interactions between learners, co-learners, teachers and researchers to take place. Smart CALL can serve as a contemporary, comprehensive lens through which data-driven methods for text analysis can be contextualised and explained. Furthermore, it provides researchers and educators with a well-balanced approach for studying CMC that can provide a more unequivocal answer to the question: "how are online interactions for educational purposes organised and is there an identifiable structure of interactional rules, procedures and conventions that govern the use of CMC in this context?", as it takes into account the person that is learning, the context in which they learn and the socialisation processes they go through along the way.

Literature Review

Researching CMC in online language learning spaces

Philp (2016), in her epilogue on new directions for researching interaction in online spaces, has pointed out that there is no clear pathway to describe and analyse interaction in CMC contexts across a vast majority of studies, and urges to draw on cross-disciplinary research to fill this gap. When focusing on researching CMC in the context of language education, one of the major caveats that arise is that analyses and evaluations of language and interaction are often neglected in favour of measuring the outcomes of tasks and assignments (Balaman & Sert, 2017). In other words, research often singles out the end product of interaction or collaboration in CMC spaces—that is, whether the learner fulfilled the requirements to obtain a grade—rather than detailing the way in which that product was made, discussed, shaped or reshaped (Zourou, 2019).

Another factor that further undermines the possibility to provide a more systemic approach to analysing CMC, elaborated upon by Sato and Ballinger (2016), is that the ways in which many institutions choose to use and promote CMC spaces for interaction, collaboration and learning are ill-founded; with approaches for integrating CMC opportunities in education often lacking evidence-based design principles. With these gaps in mind, it has become apparent that both the research field of (applied) linguistics and the field of CALL are in need of a new framework to track and map human interaction online. The present chapter, therefore, aims to initiate a conversation to rethink CMC research in language education. This process involves describing and assessing methods for text analytics with a critical eye for the affordances of the online context, comparing results of previous studies and meta-analyses, and using this knowledge to form a new basis for evaluating and integrating CMC spaces in education. At the same time, there will be a focus on approaches that allow us to measure and visualise the features of Smart CALL (i.e., personalisation, contextualisation, and socialisation), how they take shape in online interactive spaces and how they come to the foreground in the interaction process.

Modus operandi

In his review of the state-of-the-art, Carr (2020) has argued that there has been a continuous strive for novel ontological approaches for studying and visualising the ways we interact in a virtual world. And yet, as Walther and Valkenburg (2017) have pointed out, the field lacks a thorough theoretical and empirical modus operandi to analyse online interactive processes. This lack of established context-specific theories and methods to systematically analyse online language production is problematic since CMC is omnipresent in our daily lives and has taken over as one of the main forms of interaction in our education systems (cf. special issue of SiSAL Journal, 11(3)).

One example of an existing approach under scrutiny is computer-mediated discourse analysis (CMDA). This method has taken a more interdisciplinary approach to CMC text analytics over the years, hinging on, among others, the description of structure, meaning, interaction management and social phenomena (Herring, 2004). Nevertheless, leading CMDA scholars have mentioned their struggles to keep up with accurately describing interaction within ever more complex, multimodal CMC spaces that have emerged over the years. This has raised the question among them "whether CMDA is still relevant in the age of multimodal CMC" (Herring, 2019, p. 28).

Carr (2020) proposes to focus less on the term "computer" in our analyses of CMC, and to, alternatively, focus on studying the ways in which technology has become part of our social fabric; thus studying how it is used to "mediate" communication. He further asserts that giving priority to mediation rather than to the devices, programs or spaces that facilitate communication, can help us realign the field and develop more robust modus operandi for CMC text analysis. Recently, more quantitative methods for CMC text analysis have emerged that focus on analysing and visualising mediation, where various linguistic or pedagogical aspects (such as recurring topics of interest or self-regulated learning features) are taken as structural units to analyse interconnectivity, interdependence and structural integrity of interactive groups online (Peeters, Saqr, & Viberg, 2020). In line with these recent developments, this chapter will further highlight some of the opportunities quantitative approaches provide for CMC text analytics in the context of Smart CALL.

Quantitative methods in CMC text analytics

The adoption of quantitative linguistic methods to analyse CMC text has provided new opportunities to synthesise research findings in recent years. A topic of interest that has come to the foreground, for example, centres around determining if interaction sequences follow a particular structural path in CMC contexts. It has been found that turns at talk, for instance, do not randomly follow each other, but cluster together so that they become "sequentially meaningful" (Farina, 2018). In other words, when people are sharing messages or posts online, they perform actions which can generate other actions, which give relevance to actions performed earlier, or which can trigger particular responses (Tudini & Liddicoat, 2017). Researching this type of "sequence organisation" in CMC contexts has rapidly gained ground (Farina, 2018) and has enabled researchers to identify overarching structures and analyse recurring patterns within text-based CMC. It has also allowed researchers to start and make predictions on the range of responses a certain message can trigger in a CMC text environment (Peeters, Saqr & Viberg, 2020).

Nevertheless, when dealing with big amounts of data, it becomes increasingly dikcult to see and map the patterns that are arising. It is, therefore, necessary to bring together methods from (applied) linguistics, digital conversation analysis and mathematics to describe, calculate and visualise patterns within interaction sequences. In doing so, it becomes possible to empirically determine the behaviour and function of the different linguistic elements we observe, and do so across different data sets and corpora (Peeters, 2018, 2019).

One of the possible new pathways in the quantitative analysis of CMC, which coincides with current research on peer interaction and CALL, involves the use of quantitative measures—mostly integrated within mixed-methods approaches—to analyse the range and reach of language use, interaction and collaboration. Abe and Roever (2019), for example, found in their study on the development of interactional competence that foreign language learners in text-chats only use a narrow range of suggestions or “proffers” to find a solution in task-based activities. In doing so, the researchers have started to uncover how learners tend to give rise to and shape their online interactive process in a CMC space. Deng *et al*. (2019) and Yang and Farley (2019), furthermore, have designed similar studies in which they scrutinise the internal linkage, structure, and logic of online group discussions to determine how the online exchange leads to a range of solutions or outcomes to specific challenges or tasks.

While these studies rightfully employ new quantitative measures to categorise and synthesise the language that is produced in online spaces, they are not able to determine which of the elements that they have distinguished may affect prototypical sequencing, structure or logic in CMC. There is no mention of the linguistic elements that might cause substantial changes in the structure of the interaction thread, for example, and which elements might be peripheral in this regard. Having this information at our disposal, however, could change our understanding of online interaction and collaboration in a CMC space completely, especially if it enables us to determine which elements embedded within CMC text may cause fundamental changes in people’s online communicative behaviour, for better or for worse.

The reason why these studies do not do this is because of a methodological caveat, similar to what can be observed in the CMDA tradition. Using linguistic and statistical analyses do not allow researchers to empirically determine how the elements that have been distinguished in CMC text are interconnected, nor if any of them affect the frequency or behaviour of other elements within the data set. As an example, it is unknown if there are certain topics that are predominantly used to initiate conversations in these studies. It also remains unclear whether certain messages prototypically generate more answers than others, whether those answers follow logically from the initial message, whether they commonly tend to generate sub-questions and sub-threads or whether they can cause communication breakdown.

To do so, these studies would have needed a method to model pairwise relations between the elements that they had described, as can be found in the mathematical branch of graph theory: social network analysis (Peeters, Saqr & Viberg, 2020; Scott, 2017). Applying the principles of graph theory to text-based data has become a new pathway to map language-in-use. In the present chapter, it is, therefore, proposed to apply this mathematical tool to CMC-text and analyse if it is a viable method to study, map and structure the patterns within online communication and determine whether it enables us to make new evaluations of the "effectiveness of CMC" (Lin, 2015) and, potentially, revisit, or reinterpret, earlier findings in the field.

Creating linguistic networks

In the humanities and social sciences, social network analysis methods have been applied to represent relationships between actors or entities, and to analyse the significance of any patterns that might emerge between them (Scott, 2017). In most cases, this involves analysing how people connect with each other, which includes how often they interact, how many people they interact with and how fast information can be shared among them. The interactions between users can then be drawn up as a network in which actors are represented by nodes and the interaction, or connections, between them as edges (Saqr & Nouri, 2020). However, depending on the corpus or data set, it is possible to branch out and analyse "what is said" rather than on "who is saying it." A focus on mediation, for instance—that is, a focus on the message, on how it is conveyed, and on how it fits within interaction sequences—might shed more light on the internal structure of CMC in this regard. In other words, social network analysis can be used to create linguistic networks in which linguistic elements and the relationships between them act as the main topic of research.

Just like any other network, a linguistic network requires actors, represented by nodes, and connections between actors, represented by edges. In recent research, self-regulated learning tactics have been used as a coding scheme for such a CMC analysis, where researchers distinguished a number of self-regulation activities (including planning, applying feedback and reflecting) in CMC text and analysed how these different activities interrelated and depended on one another (Peeters, Saqr & Viberg, 2020). In another study, network measures were used to decipher the structure of a self-regulated network for learning, highlighting the importance of activities such as social bonding and acculturation in groups of new language learners at university (Saqr, Viberg & Peeters, 2021). Next to learning activities, linguistic and discourse elements could function as data points as well. Topic analysis, sentiment analysis or agreement classifications (Cambria *et al.*, 2013) could, for example, serve as input for further network analyses.

In order to show how such an analysis can be performed and which results it might yield, the present chapter provides an example case, using data from a study performed at a Japanese private university (Peeters & Mynard, 2019, 2021). The focus will lie on some key aspects of the social network analysis approach, including the need to incorporate time measures in such an analysis, as well as on some of the basic building blocks, including the creation of heatmaps.

Methodology

Context and participants

The data originated from a study at Kanda University of International Studies (KUIS), where a group of foreign language learners (n = 188) took part in an effective learning module at the Self-Access Learning Center (SALC), part of the institution. The modules were designed to help learners develop necessary skills to manage and regulate their language learning such as planning, managing resources and applying different learning strategies, making and following through on learning plans, working with peers, teachers and learning advisors, and evaluating their own progress (see Curry *et al.*, 2017, for details). The modules were taught in English and ran for one semester, during which learners worked their way through a number of units in which they could systematically draft learning plans, reflect on their weekly activities and report back to their peers and to learning advisors. Google Classroom was integrated into the module to give learners the opportunity to consult with their peers at any given time. Google Classroom was chosen because it was already well-integrated into other courses of the language curriculum, which lowered the threshold for participation. Every two weeks, the module pack included a reminder to motivate learners to share their reflections or questions with their fellow students on Google Classroom. These small exercises to share their thoughts were optional and were meant to keep students aware of the online forum. No teachers or learning advisors were present in this Google Classroom. It functioned as a peer collaboration and peer review space.

Participants were first-, second- and third-year students at the university. The majority of them were part of the English department (Group 1, n = 78), while others were part of the department of Chinese, Spanish and Korean (CSK) (Group 2, n = 61) or the department of International Communication (Group 3, n = 39). Students participated voluntarily and were grouped into three Google Classrooms based on their departments. There were no requirements for students to interact with their fellow learners online and their participation online would not affect their mark for the module. Because all students are required to take English classes and achieve certain scores on international tests before they can graduate from the university, no matter the language major they follow, the language of instruction of the effective learning module is English. As a result, all interactions online were in English too. All students had Japanese as their first language. Students' English proficiency levels tended to range between intermediate and upper-intermediate when entering the module. Informed consent was obtained from all participants in the study before any data was collected.

Data and analysis

Students generated 697 posts on the Google Classroom forum (384 initial posts and 313 comments). CMC data was collected using an application programming interface through which textual data was downloaded, including metadata such as time stamps, user IDs and like counts. The data set was fully anonymized before any analysis was conducted. Using the annotation software NVivo, recurring topics that dealt with learners' effective learning process were listed in a code book through several coding phases (DeCuir-Gunby, Marshall, & McCulloch, 2011). In the end, a team of two coders compiled a code book with twenty-four recurring themes and motifs (see Appendix and Peeters & Mynard, 2021, for details) including, among others, discussing planning and timing, identifying learning strategies, reflecting on performance, reflecting on materials and resources, sharing personal stories and expressing gratitude (Figures 3.1 – 3.2).

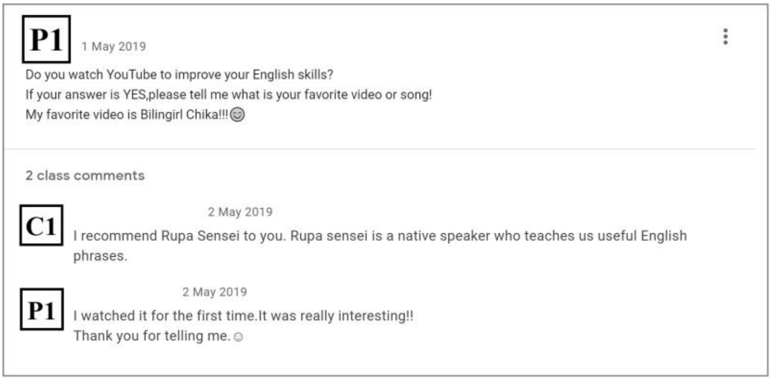

Figure 3.1 *Example of a conversation between two students (Group 1) in which they ask for information on learning strategies and resources, and share their recommendations, acknowledgements and expressions of gratitude. P1 stands for the student who made the initial post, C1 stands for the student who made the first comment.*

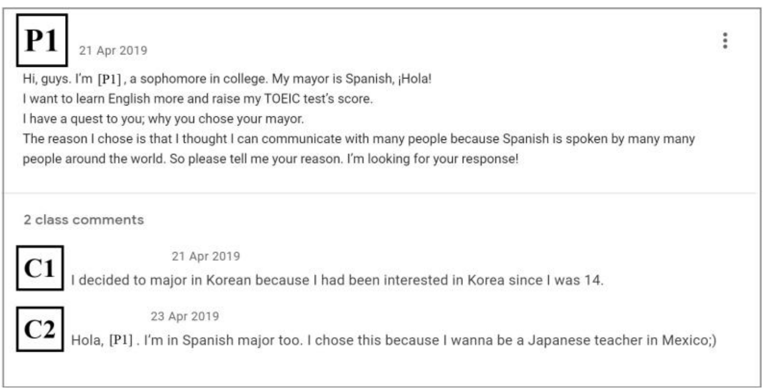

Figure 3.2 *Conversation between three students (Group 2) on Google Classroom in which they introduced themselves, discussed their learning goals and shared their personal stories.*

Using time stamps, an overview is presented of the number of posts and comments students in each Google Classroom shared each day. Using the coded data points, heatmaps were created using the technical computing program Wolfram Mathematica.

Results

In the results section, special attention is paid to a number of data visualisation approaches such as interaction heat maps that can help educators and researchers to start making sense of CMC. The information obtained can be used to improve our understanding of foreign language learners' online interaction and collaboration patterns, as well as improve the integration of CMC spaces in education. Two aspects, in particular, will be highlighted: the presence of burst patterns and the importance of temporality in CMC analysis on the one hand, and the relations that can be drawn between the coded data points in the CMC data set on the other.

Burst patterns in online collaboration

Within learner analytics studies, as well as in CMC text analytics, the time factor—that is, questions revolving around when and for how long actions and activities occur—has come to the foreground in recent years (Baker *et al.*, 2021; Saint *et al.*, 2020). Also in this study, taking into account temporal aspects of interaction and collaboration are key. The following timelines (Figures 3.3 – 3.5) illustrate why these temporal aspects matter when researching CMC in education. In all three figures, burst patterns could be observed with peaks at times when students were very active, and valleys where students were less engaged. What also could be observed for all three groups was that these bursts faded and lost power and intensity, meaning that students became less and less active as time went by.

Group 1 (English department) saw three major peaks, situated in the first half of the effective learning module (Figure 3.3). The weeks where there was a lot of activity correspond with the weeks where students were required to hand in reflections and where they were reminded that they could consult with their peers online. During the days between peak one and peak two, students remained active throughout the days. From peak two onwards, gaps started to occur. These gaps of inactivity became wider and wider as the module progressed. The same patterns could be observed for Group 2 (CSK department) and Group 3 (IC department).

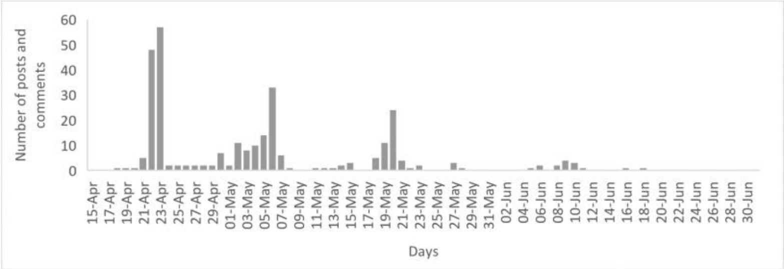

Figure 3.3 *Number of posts and comments made by students (English department) over a period of two and a half months.*

In Group 2, which had about the same number of students participating, the same bursts can be observed around the same time as Group 1 (Figure 3.4). The first burst in Group 1, however, reaches a higher peak, while the onset and offset of the first peak in Group 2 is more pronounced. The time between the first and the second burst in Group 2 sees one small gap of inactivity around the second week of the module. Peak two and peak three do not reach the same highs as the ones in Group 1. In comparison, there is little to no activity after the final peak.

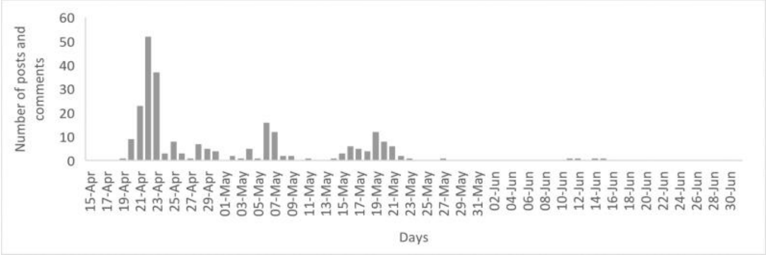

Figure 3.4 *Number of posts and comments made by students (CSK department) over a period of two and a half months.*

In Group 3, which had about half the student number compared to Group 1 and Group 2, the same burst patterns can be observed (Figure 3.5). Here the onsets and offsets of the peaks are also more pronounced compared to Group 1, while there are more gaps noticeable between the first, second and third peaks. There is still some student activity occurring after the third peak, relatively similar to Group 1.

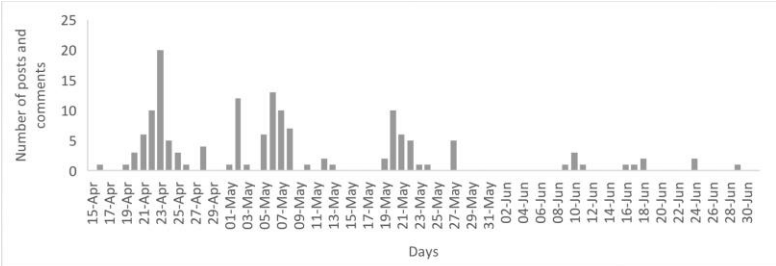

Figure 3.5 *Number of posts and comments made by students (IC department) over a period of two and a half months.*

These burst patterns show how periods of active engagement alternate with periods of inactivity in a CMC space. When analysing CMC through network analysis methods, it is, therefore, advised to integrate this information in the analysis. If not, nuance might get lost as interaction and interaction patterns that might change over time are not accounted for. For example, in the case of the present study, learners might address different topics or issues at different times as they grow accustomed to the tasks, their peers and the learning environment (Peeters & Fourie, 2018). Creating one overall picture (e.g., an aggregate network) could blur the lines between these phases, and between possible changes and developments. These burst patterns, therefore, can provide an indication of how to divide up the analysis, resulting in the creation of multiple networks dependent on active time intervals, rather than creating an aggregated picture.

Interaction heatmaps

An approach that can help educators and researchers to make sense out of CMC data is the creation of heatmaps. Heatmaps provide information on where most of the activity is concentrated in collaborative processes and can serve as the basis for the visualisation of more elaborate networks. When working with coded CMC data, like in the present study, all codes can be arranged on two axes, creating a matrix. Using simple "coding and counting principles," we can map the number of times certain codes are part of the same conversation thread in the matrix. In other words, these kinds of adjacency matrices provide information on how many times connections are made between codes. Looking at horizontal and vertical alignment (in which the vertical axis represents the "initial post" in the conversation thread and the horizontal axis represents the "comments"), we can start distinguishing patterns.

In Group 1, it can be observed that there are two major topics of interest that dominate in the comment section of conversation threads (Figure 3.6). These are "asking for acknowledgement" after giving or suggesting an answer to a posed question (n = 101) and "expressing gratitude" (n = 56). The lit-up columns also indicate that these comments can be linked to a variety of initial posts. "Asking for information on resources" (n = 64) and "discussing learning goals and objectives" (n = 57) were well-connected topics in the initial posts in conversation threads. In the comments to questions that revolved around "asking for information on resources", learners most commonly "share personal resources" or materials they have used themselves (n = 20). The links between these two topics were most common in the collaborative process. Interestingly, learners shared more personal resources than resources that were available through the university website or university library (n = 3).

In Group 2, "asking for acknowledgement" after giving or suggesting answers was also the most common comment in conversation threads (n = 141), followed by "expressing likes" (n = 124), which revolved around expressing how much learners liked using certain materials or resources in the learning environment or how much they liked comments or resources shared by others (Figure 3.7). While the column "asking for acknowledgements" is still lit up, we can also observe a cluster of "expressing likes" and "leisure talk" in the bottom right-hand corner, which designates comments that mention going on vacation, spending time on hobbies or talking about pastime. When looking at the initial posts these comments can be associated with, we can see that they most commonly appear in conversation threads in which the initial post revolved around the same topics of interest (i.e., "expressing likes" and "leisure talk"). This group seemed more focused on creating social bonds, compared to Group 1, as the topics in initial posts commonly revolved around "discussing personal stories/introductions" (n = 82) and "leisure talk" (n = 74).

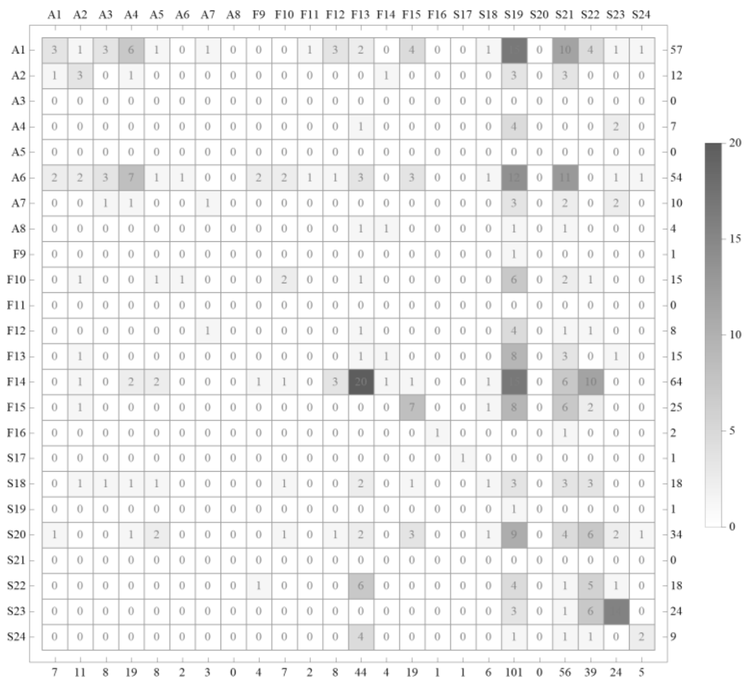

Figure 3.6 *Aggregate heatmap of the links between posts and comments made by students (English department) over a period of two and a half months.*

Lastly, Group 3 had less-defined hubs of activity (Figure 3.8). Overall, "asking for acknowledgement" (n = 14) was the most common topic of interest in the comment section, followed by "expressing likes" (n = 13) and "leisure talk" (n = 12). Most initial posts addressed "leisure talk" (n = 22) and "evaluating strategies" (n = 18), where learners reflected on their use of certain learning strategies and gave their assessment of how well it worked for them or how well it fitted their needs. A small hub can be observed, where posts on "leisure talk" received comments on "leisure talk" and on "expressing likes."

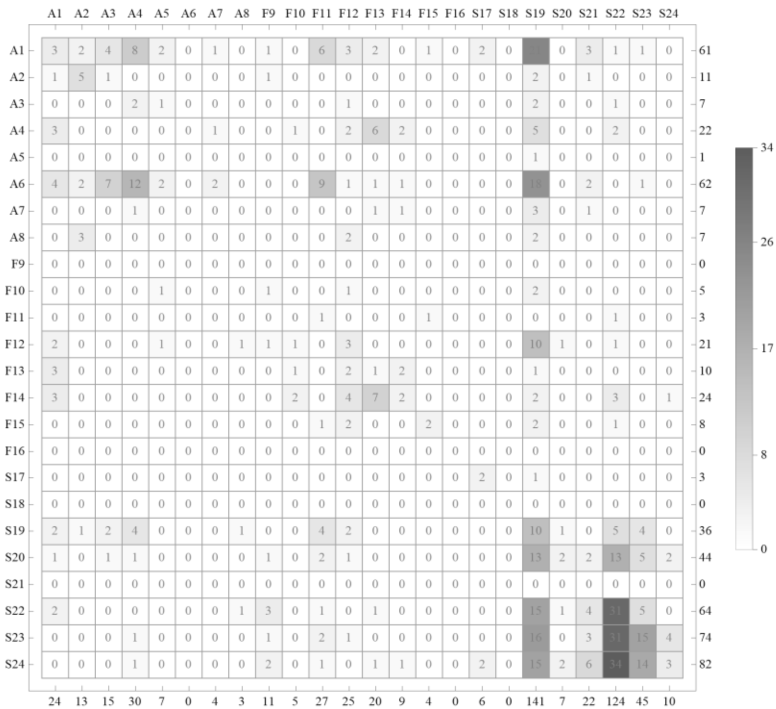

Figure 3.7 *Aggregate heatmap of the links between posts and comments made by students (CSK department) over a period of two and a half months.*

Time-bound heatmaps

As indicated in the literature review, the aspect of time can be a key factor in understanding CMC dynamics as well as collaboration within CMC spaces. In the present study, based on the burst patterns, we can distinguish three main periods in which students were actively engaging with the module, with the materials and with each other. For these three periods, three heatmaps were made, providing an overview of the hubs and the focal points in the interaction process at certain times. As an example, we will look at Group 1. For the first period (which corresponds with the first two weeks of the module), the heatmap shows 187 connections between different topics of interest (Figure 3.9). From the start, it becomes clear that the heatmap shows more variation, with different areas lighting up, compared to the aggregate heatmap (Figure 3.6). Similar to the aggregate heatmap, "asking for acknowledgement" (n = 41) and "expressing gratitude" (n = 29) are the most common topics in the comment section across a variety of interaction threads. "Discussing learning goals and objectives" (n = 41) and "evaluating strategies" (n = 39), however, are the most commonly found initial posts. This deviates from the aggregate heatmap, where "asking for information on resources" was most commonly found. The middle column "sharing personal resources" is also prominent, with the strongest link to "asking for information on resources," which is similar to the aggregate heatmap for Group 1 (Figure 3.6).

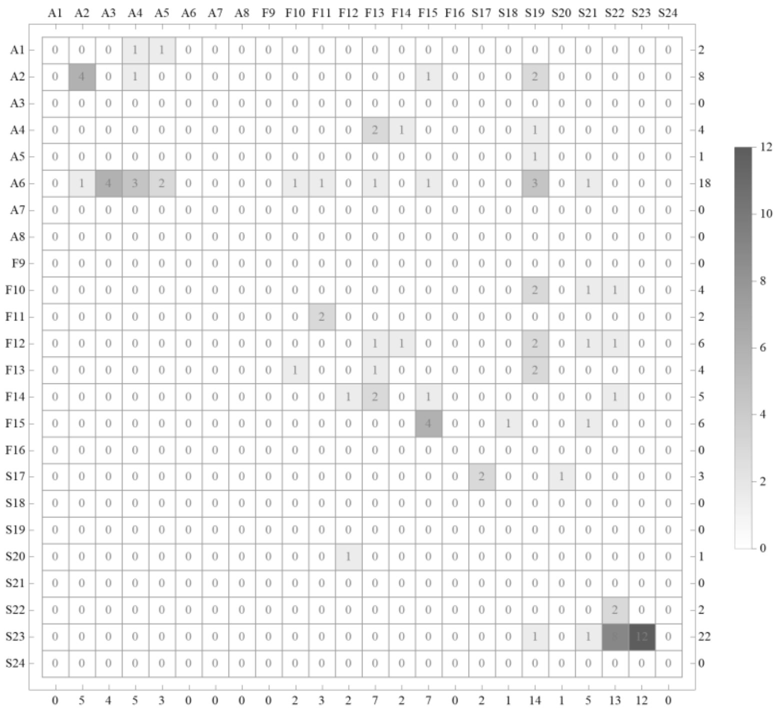

Figure 3.8 *Aggregate heatmap of the links between posts and comments made by students (IC department) over a period of two and a half months.*

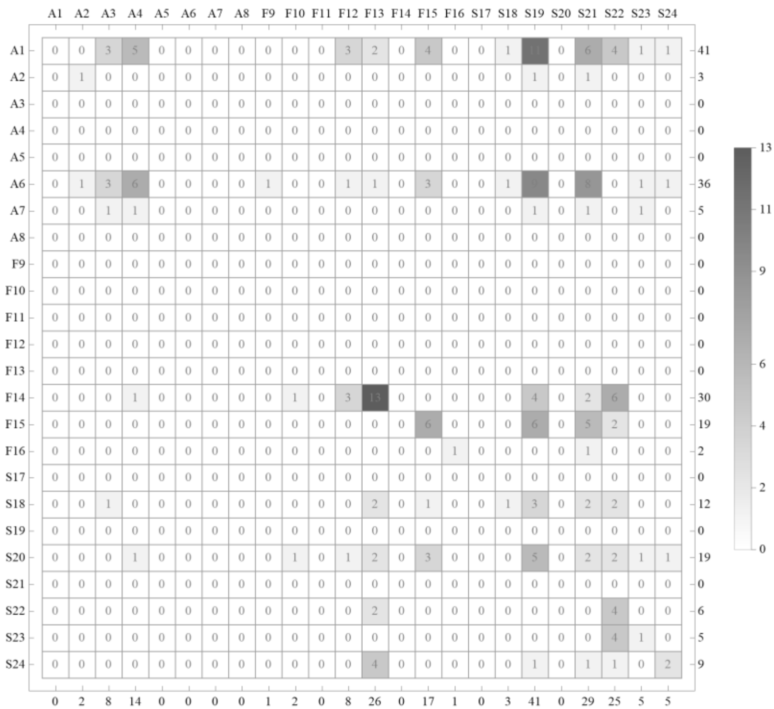

Figure 3.9 *Heatmap of the links between posts and comments made by students (English department) over the initial period of two weeks.*

Some notable similarities and differences can be seen for the second burst period of two weeks (Figure 3.10). Both columns of “asking for acknowledgement” (n = 24) and “expressing gratitude” (n = 19) are still lit up, but these two topics could now be found more often in conversations that revolve around “asking for information on resources”. The strongest link here is “leisure talk”, which was a prominent comment in conversation threads that followed posts on the same topic. It can be noted that, in the first period, there was little to no interaction on this topic. The strongest link in the first period (i.e., comments on “sharing personal resources” to posts on “asking for information on resources”) had faded away.

In the final period of six weeks, the role of “asking for acknowledgement” (n = 36) holds strong, while “expressing gratitude” (n = 8) fades into the background (Figure 3.11). The strongest links could be found between “asking for acknowledgement” and “asking for information on resources” where students tended to give their opinions or remarks, followed by questions on whether or not these were useful or helpful.

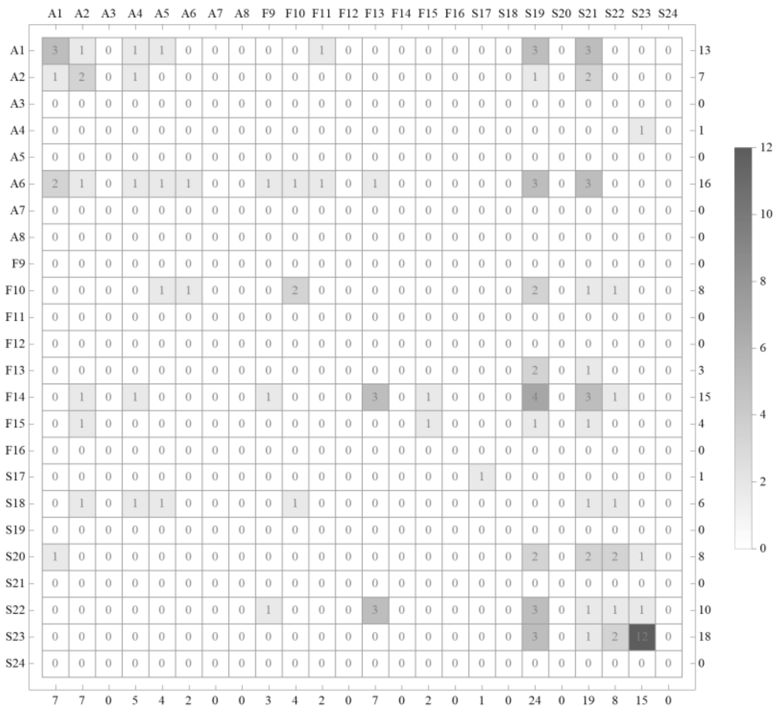

Figure 3.10 *Heatmap of the links between posts and comments made by students (English department) over the middle period of two weeks.*

Overall, these heatmaps better illustrate the dynamics that occurred in a CMC environment for language learning. While the aggregate heatmap for Group 1 showed acknowledgement and gratitude as the most prominent responses to a variety of posts, we can see that over time, showing gratitude fell out of favour. It also became apparent that, during the first period, learners were more focused on discussing learning goals and strategies, while over time the focus moved to resource management. Interestingly, during the second period, social bonding came to the foreground very prominently, while during the initial and final periods of the module, this faded into the background. The discussion will focus on the importance of mapping these dynamics, paying special attention to how these methods can be applied to the principles of Smart CALL.

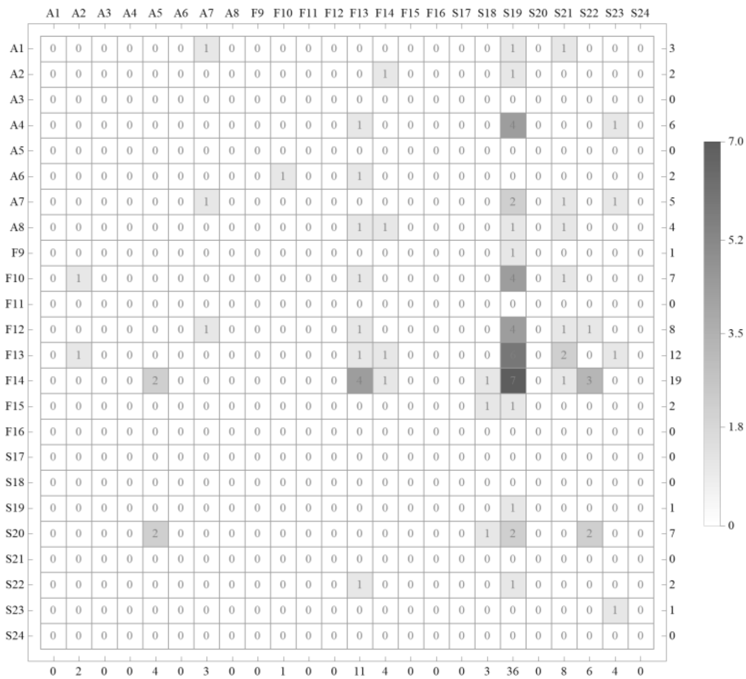

Figure 3.11 *Heatmap of the links between posts and comments made by students (English department) over the final period of six weeks.*

Application to Smart CALL

Mapping CMC dynamics within a number of time frames allows educators and researchers to distinguish between different processes and stages of the learning process. As a first step, it is vital to determine appropriate time frames for such an analysis (Gašević *et al.*, 2017) in order to organise activities and events into meaningful groups. The burst patterns that could be observed in this study and in similar studies in the field (e.g., Chen & Poquet, 2020; Saqr & Nouri, 2020) can serve as indicators to divide the interaction and collaboration process online into different clusters or cycles.

Heatmaps that follow these clusters or cycles provide more accurate visualisations of online collaborative processes in general, and the dynamics within CMC text in particular. These visualisations can assist educators and researchers to better observe learners' learning process, determining, for example, if they are able to meet pre-set requirements and, thus, can advance properly. This monitoring also allows them to assist and support students faster and more accurately (Peeters, Viberg & Saqr, 2020). In doing so, they can prevent students from bumping into avoidable hurdles by making them aware of the specific pitfalls they might encounter on their path. This kind of awareness raising can help students that might run into trouble in their learning trajectory to adjust, plan and reflect on their activities and actions better. Similarly, on a group level, it is possible to determine if group dynamics follow logical paths of connecting, negotiating and socialising with others (Peeters, 2018). Since the main reason for integrating online platforms into the language learning curriculum is to provide learners with an environment for support, collaboration and growth (Zourou, 2019), monitoring if all necessary components are present for interaction and learning to take place can form a key role in assessing the efficacy of CMC spaces in education.

In this regard, CMC text analytics can inform educators and researchers on the ways different aspects of socialisation within Smart CALL take shape in online groups. Socialisation refers to the ways in which technologies and learning environments afford meaningful interaction, such as interaction amongst learners. The coding methods applied in this study, as well as the methods applied for measuring the interrelation between the different codes through heatmaps, have created opportunities to visualise how learners of a foreign language can potentially expand their horizons, dialogically improve their skills and make use of the target language (Sato & Ballinger, 2016). These methods also form an opportunity to map how learners tend to gain experience in negotiating content, discover new resources and develop their critical literacy skills; all necessary components of becoming life-long learners.

As these approaches can enable us to see the links between the different elements of CMC text, we can start to determine how a successful peer network is built up and how interpersonal relationships are established over time when students try to form an online community for academic purposes (Peeters & Pretorius, 2020). Analysing key components of CALL, such as socialisation within CMC, in a structured, replicable way, therefore, is a much-needed next step in optimising the smart integration of online tools and platforms in language learning contexts.

This study is set up in line with earlier research which has shown the positive impact of socialising novice students in language learning contexts (Curry *et al*., 2017; Sato & Ballinger, 2016). What is new, however, is that the application of social network analysis principles to analyse and visualise the process of socialisation and information exchange in CMC text allows us a look into the wider semiotic contexts in which the learning process is taking place, which is a critical aspect of the pedagogical use of online platforms for language learning (Zourou, 2019). In the present case, it allowed us to determine how socialisation unfolds while students collaborate on a number of self-regulated learning tasks through Google Classroom. It also allowed us to see the interplay between different aspects of socialisation over time as the focus of interaction and collaboration changed from discussing learning goals to creating social bonds and, eventually, resource management. Given the context in which these learners were operating (i.e., in an effective learning module), it is both informative and educational for educators and researchers to be able to observe this shift between academic acculturation, identity construction, and organisation.

Conclusion

The first purpose of this chapter was to investigate if applying some of the principles of social network analysis to CMC text would allow us to describe and analyse interaction in CMC contexts in such a way that we can start making new evaluations of the “effectiveness of CMC” (Lin, 2015). Taking into account time measures in the analysis, based on the burst patterns that could be observed in participants’ active engagement, proved to be a valuable first step in this regard. As a second step, adjacency matrices proved to be valuable sources of information to create heatmaps on the interplay between the different aspects of collaboration and learning that were found in earlier coding processes (Peeters & Mynard, 2021). These matrices can, furthermore, serve as the basis for more elaborate social network analysis measures such as the creation of weighted, directed networks.

For the purpose of creating opportunities to better understand CMC in the context of Smart CALL, this study has shown that the dynamics within interaction and collaboration online change over time and that accounting for these dynamics can enable educators and researchers to better map and observe processes such as socialisation. These methods, furthermore, can help to improve both the design of CMC spaces for education—as they provide an overview of the dynamics that are present or absent in a certain space—as well as the support mechanisms that educators can provide throughout the learning process of their students.

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Appendix

Table 3.1 *Overview of the code book (Peeters & Mynard, 2021).*

Code	Strategies	Metastrategies	Strata	SARC
A1	Discussing learning goals and objectives, including personal goals	Planning	Meta-cognitive	Awareness of approaches to learning
A2	Discussing planning and timing	Planning	Meta-cognitive	Awareness of approaches to learning
A3	Identifying strategies	Orchestrating strategy use	Meta-cognitive	Awareness of approaches to learning
A4	Trying out strategies	Orchestrating strategy use	Meta-cognitive	Awareness of approaches to learning
A5	Asking for information on the use of tactics and strategies for learning	Orchestrating strategy use	Meta-cognitive	Awareness of approaches to learning
A6	Evaluating strategies	Evaluating	Meta-cognitive	Awareness of approaches to learning
A7	Reflecting on performance	Evaluating	Meta-cognitive	Awareness of approaches to learning
A8	Discussing the Module pack and reasons for taking the Module	Evaluating	Meta-cognitive	Awareness of approaches to learning
F9	Reflecting on materials and resources	Evaluating	Meta-cognitive	Awareness of facilities, roles and resources
F10	Discussing the content of materials and resources for the course	Obtaining and using resources	Meta-cognitive	Awareness of facilities, roles and resources
F11	Sharing resources: spaces and people	Obtaining and using resources	Meta-cognitive	Awareness of facilities, roles and resources
F12	Sharing resources: materials available at the institute	Obtaining and using resources	Meta-cognitive	Awareness of facilities, roles and resources
F13	Sharing resources: personal materials	Obtaining and using resources	Meta-cognitive	Awareness of facilities, roles and resources
F14	Asking for (info on) resources	Obtaining and using resources	Meta-cognitive	Awareness of facilities, roles and resources
F15	Sharing experiences, tips and tricks about learning trajectory	Organising	Meta-social	Awareness of facilities, roles and resources
F16	Solving a practical or technical problem	Organising	Meta-social	Awareness of facilities, roles and resources
S17	Expressing emotions on performance	Evaluating	Meta-affective	Awareness of self
S18	Reflecting on (choices made in) learning trajectory	Monitoring	Meta-affective	Awareness of self
S19	Asking for acknowledgement	Monitoring	Meta-motivational	Awareness of self
S20	Providing acknowledgement or positive reinforcement	Paying attention	Meta-motivational	Awareness of self
S21	Expressing gratitude	Paying attention	Meta-motivational	Awareness of self
S22	Expressing likes	Paying attention	Meta-motivational	Awareness of self
S23	Leisure talk	Paying attention	Meta-social	Awareness of self
S24	Discussing personal stories / introductions	Paying attention	Meta-social	Awareness of self