Using Psychological Networks to Reveal the Interplay between Foreign Language Students' Self-Regulated Learning Tactics

Mohammed Saqr [a,c], Olga Viberg [a], Ward Peteers [b]
[a] KTH Royal Institute of Technology, Lindstedsvägen 3, 10044 Stockholm, Sweden
[b] Kanda University of International Studies, 1-4-1, Wakaba, Mihama-ku Chiba-shi, Chiba-ken, Japan
[c] University of Eastern Finland, FI-80100 Joensuu, Finland

Abstract

Students' ability to self-regulate their individual and collaborative learning activities while performing challenging academic writing tasks is instrumental for their academic success. Presently, the majority of such learning activities often occur in computer-supported collaborative learning (CSCL) settings, in which students generate digital learner data. Examining this data may provide valuable insights into their self-regulated learning (SRL) behaviours. Such an understanding is important for educators to provide adequate support. Recent advances in the fields of learning analytics (LA) and SRL offer new ways to analyse such data and understand students' dynamic SRL processes. This study uses a novel psychological network method, i.e., Gaussian Graphical Models, to model the interactions between the students' SRL tactics and how they influence language learning in a CSCL setting for academic writing. The data for this study was generated by first-year foreign language students (*n*=119) who used a Facebook group as a collaborative space for peer review in an academic writing course. The theoretical lens of strategic self-regulated language learning was applied. The findings show a strong connection between the following tactics: writing text, social bonding and acknowledging. Strong connections between students' reflective activities and their application of feedback, as well as between acculturating, organising and using resources were also identified. *Centrality measures* showed that acculturating is most strongly connected to all other tactics, followed by acknowledging and social bonding. *Expected influence centrality measures* showed acculturating and social interactions to be strong influencers. Students' academic performance and their use of tactics showed little correlation.

Keywords

Psychological networks, Gaussian Graphical Models, self-regulated learning, foreign language learning, computer-supported collaborative learning

1. Introduction

Academic writing is a vital aspect in a student's learning path as it is one of the major ways to achieve several academic goals, enhance critical thinking skills, stimulate creativity, and create awareness, knowledge and skills about the use of academic and professional discourse [1]. However, it is a challenging and complex learning activity in which learners' ability to self-regulate their learning process is critical for their study success [2]. The ability to self-regulate their own learning empowers students to take control of their learning process, including the choices they make, the strategies they use and the resources they seek out, and prepares them for lifelong learning [3]. Even though self-regulation is mostly seen as a task of the learner, students benefit from receiving support in terms of the development of their self-regulated learning (SRL) strategies, skills and knowledge. As shown in earlier research, its principles can be learnt and taught, and, because of this, a learner's SRL development should be tracked and assessed [3]. In doing so, we ensure that educators will be able to provide apt, adequate and relevant support mechanisms throughout a student's learning trajectory [4, 5].

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

Lately, significant attention has been paid to how online collaborative learning spaces can enable and foster language learners' autonomy development, their self-regulation in learning and such skills as writing and speaking in second and foreign language learning [6, 7]. Yet, a paucity of research that has been performed to understand language learners' SRL behaviour remains in computer-assisted learning settings such as learning management systems or social networking sites (SNS) [8]. While recent studies have increasingly started to measure language students' SRL behaviours through the analysis of student-generated (log) data [9], there are still many studies that solely rely on self-report instruments to analyse and assess SRL [10].

In recent years, the context of computer-supported collaborative learning (CSCL) has allowed students to generate a range of new types of digital (log) data, the careful analysis of which can offer researchers and practitioners new valuable insights into foreign language students' SRL processes. This approach would in addition reduce the need for subjective assessment methods (e.g., surveys and think-alouds) [5] to measure and understand students' SRL processes. A shift has emerged to measure students' SRL behaviour with learning analytics (LA) methods, including multimodal data from learning management systems or other online platforms such as SNSs. Among the methods used to track learners' SRL processes, scholars have applied frequency analysis (e.g., [11], network analysis [4], and process mining techniques (e.g., [12]).

This exploratory study aims to further contribute to this emerging trend by focusing on the application of a (to the educational research field) novel psychological network method of Gaussian Graphical Models (GGMs; an undirected network of partial correlation coefficients) to study foreign language students' SRL activities / tactics in the setting of an academic writing course. SRL *tactics* refer to the specific, applied ways in which a strategy (e.g., planning or time management) is being employed to meet a goal in a specific learning situation [13].

Networks are used across similar studies to represent different entities (referred to as nodes), and the relationships between them (referred to as edges). The nodes can represent various structures or elements (e.g., humans, cities, countries, or concepts), while edges can be friendships, roads or influence. Psychological networks are a special type of networks where the nodes are variables and the edges represent correlations or a level of dependence between nodes [14, 15]. Psychological networks have been increasingly adopted in psychology and behavioural research to model the interactions and relationships between constructs including behaviour, emotions and mental phenomena (e.g., [16, 17]). The approach stems from the conceptualisation of human behaviour as a complex system with multiple elements that interact and influence each other. This is also the case for education where, for example, learners' goal setting activities often relate to their task management and engagement in the learning process, and both can be linked to their self-reflection activities which, in turn, influence the process. Such interactions cannot be studied individually, but need to be combined in a robust holistic model that maps the various elements of the process. Therefore, in this study, we argue that the application of psychological networks can be a valuable approach that would broaden our understanding of these dynamic interactions in learners' SRL development. In contrast to the commonly used network models (e.g., social network analysis), psychological networks offer rigorous probabilistic network models that account for spurious correlations and conditional independence. Psychological networks have a large battery of confirmatory statistics to verify the estimated networks and offer a hypothesis generation model that helps advance our understanding of the (learning) process [16, 18].

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

In summary, this study aims to test the application of GGM methods to uncover the dynamics of foreign language students' SRL tactics when collaborating online with their peers on academic writing tasks. The following research questions have been formulated:

1. *What information can be obtained from analysing foreign language students' SRL tactics in their academic writing process using Gaussian Graphical Models?*
2. *How does academic achievement relate to students' approaches to self-regulated language learning?*

2. Background

2.1. Self-regulation and academic writing

Academic writing in the target language is a complex and challenging process in which learners of second and foreign languages need to grow accustomed to a wide range of linguistic rules, interactional goals and socio-cultural contexts [19]. In order to do so successfully, learners can benefit from applying self-regulated learning strategies in their writing practice. Self-regulation in writing refers to "self-initiated thoughts, feelings and actions that writers use to attain various literary goals, including their writing skills as well as enhancing the quality of the text they create" [20, p.76]. Research has shown that learners who received SRL strategy-based writing instruction were able to use a wider range of SRL strategies and reported increased levels of performance and linguistic self-efficacy [21, 22].

At present, a considerable number of academic writing instruction, including related tasks and learning activities, often occur in CSCL settings [33]. It is in this context that the present study aims to use GGM methods to explore foreign language learners' use of SRL tactics based on the log data they have generated.

2.2. Network representation

Networks offer a rich framework for the analysis of different phenomena and therefore, have been used extensively over the years to understand learners' behaviour in education [23]. Social network analysis (SNA) has, for example, been used to study interactions between students and teachers, interactions between students and learning materials, and co-enrolment in similar subjects [24, 25]. Network representations in learners' networks can be considered rather straightforward: the nodes represent learners and the edges among them are the connections they make by verbal interactions or connections on online platforms [26]. Epistemic network analysis (ENA) is another network representation that has recently gained popularity to represent the interactions between different phenomena and in particular, the utterances in students' interactions (e.g., [27, 28]). The nodes in ENA are usually the phenomena under study, for example coded utterances, and the relationships between them (edges) are co-temporal representations of the codes in the same conversation. Process mining is another type of network representation that has been used to study students' SRL strategies (e.g., [11] and tactics [4]. As such, the wealth and flexibility of networks as a framework has contributed substantially to our understanding of the multifaceted aspects of learning and teaching activities and processes.

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

2.3. Gaussian Graphical Models

A psychological network approach is another method to represent the relationships among variables (coded interactions in our case), where the nodes represent the coded interactions and the edges represent the association between the variables. The associations are measured by partial correlation. A positive partial correlation between variables means that there is an association between the two variables after controlling for all other variables in the network, similar to regression models. Controlling for other variables gives a robust estimate of the association and limits the problem of spurious correlations due to confounders. For example, in a bivariate correlation, a researcher reports a positive association between coffee consumption and academic achievement, which may be due to unmeasured study time, while in psychological networks, adding coffee to the network model will show the association between study time and achievement, and not exclusively the influence of the coffee. Psychological networks are commonly reported as regularised networks by applying a shrinkage parameter that drops small and insignificant edges from the model and prevents overfitting. This is particularly important, since correlating many variables together may result in ‘noisy’ trivial correlations. Furthermore, psychological networks offer several confirmatory tests to verify the significance of edges or centrality measures.

Psychological networks models have witnessed rapid growth, improvements and refinements of the methods, interpretation, verification and rigour [16]. Such advancement has led to an increased adoption in many fields, including exploratory analysis, modelling psychological phenomena, studying human behaviour, modelling the interplay between different attitudes, and the understanding of human personality and emotions. In the field of psychology, which has also been studying individuals’ self-regulation process for decades (e.g., [29, 30]), psychological networks have contributed to the understanding of, among others, the complexity of mental disorders, i.e. modelling how symptoms of a mental disorder are interdependent. In line with the related research efforts undertaken in other fields, the application of psychological networks in the educational field would aid researchers to broaden their understanding of the conditional associations between different variables within learners’ development of SRL activities / tactics, and the application of them in dynamic online systems.

3. Methodology

This study makes use of a dataset generated by a group of first-year foreign language majors of English (n=119) as they collaborated with their peers on a Facebook group, integrated in an academic writing course at the University of Antwerp (Belgium), and which served as an online collaborative space for peer review. Learners exchanged written work and brainstormed about the different rules and principles they had to adhere to, as well as the form and argumentation of their writing, and the goals, perspectives and organisation of the course. During the 12 face-to-face contact hours for the course, learners were introduced to the foundations of academic writing and had to hand in three 300-word essays over the course of the semester. While students were introduced to the basics of peer review, there was no explicit self-regulated learning strategy-based instruction or training. Students generated 2594 posts and comments on the Facebook group over a period of three months.

Coding: Based on the Strategic Self-Regulation (S2R) model [13], including the taxonomy of cognitive, affective and sociocultural-interactive activities in learning, and using the

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

principles of digital conversation analysis [31], an exhaustive list of core (learning) activities in the conversation threads was compiled. A team of four coders part of the research group responsible for the course at the University of Antwerp coded and checked the transcripts, after which both coding errors and inter-rater reliability were discussed. Disputed codes were amended until a consensus was reached. The final code book includes the topics and the SRL tactics students addressed. The topics and tactics have been subdivided using Oxford's [13] task-based model, including the strategic forethought phase of self-regulation (i.e., *planning*, in which students plan the next steps in their writing or learning trajectory, *acculturating*, or students sharing stories, tips and tricks about the academic, cultural, social, psychological and linguistic challenges they face, and *organising*, or managing goals, objectives and requirements), the strategic performance phase (including *writing text*, where students discuss the vocabulary, jargon, grammar and structure of their essays, *writing arguments*, or discussing reasoning and logic of their text, *using resources*, where they assess the resources available to them, *social bonding*, where they talk about hobbies, free time and leisure, *acknowledging*, where they react to the input from others, and discussing and *applying feedback*, where they work with the feedback from tutors and peers), or the strategic reflection and evaluation phase (including *reflecting* on the course, the tasks and the collaboration with others).

Analysis: The frequency of each code contributed by each student was calculated. The R package Huge was used to apply Gaussianisation (applying a smoothing invertible transformation to transform the distribution as close to Gaussian as possible) for all variables to conform with the assumption of normality. We constructed a GGM, i.e. an undirected network in which continuous variables (elements of SRL in our case) are represented by nodes, and the strength of partial correlations between the variables is represented by the edges. An edge between two nodes indicates conditional dependence after controlling for all other nodes in the network, while the absence of an edge indicates that the two nodes are conditionally independent after controlling for all other nodes. In particular, a regularised partial correlation network was estimated using the R! Bootnet package (https://www.r-project.org). LASSO shrinkage [32, 16] was applied to all edges, so that the edges with minimal values would be discarded as well to account for multiple comparison problems (as there is a risk of obtaining false positive nodes by chance or by overfitting). Such technique has been shown to provide accurate models with reasonable specificity and sensitivity. The shrinkage was performed using an Extended Bayesian Information Criterion (EBIC). The package MGM was used to capture to what extent the value of a node can be predicted by its connections in the network. The root mean squared error (RMSE) and the proportion of explained variance (R2) are also reported for each node. The *strength* and *expected influence* centrality were calculated using the bootnet package for all networks. Network stability was computed using a non-parametric bootstrap method and case dropping procedure for centrality measures. Node accuracy and stability of centralities were taken into account when reporting on and interpreting the results. We generated two networks, a network with the grades included to control for the influence of academic performance on the used SRL tactics, we refer to it as the *Grade_network* and a network with only the SRL tactics used to examine the structure of the self-regulated language learning network, which we refer to as *SRL_network.*

4. Findings

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

The descriptive statistics of the coded interactions show that *acknowledging, writing text* and *writing arguments* are the most frequently employed tactics. Large standard deviations (sd) show the wide variety in the use of SRL tactics as well as their frequencies (see Table 1).

Table 1
Descriptive statistics on students' SRL tactics.

variables	mean	sd	variables	mean	sd
Acculturating	2.6	3.1	Reflecting	1.38	2.61
Acknowledging	5.41	6.11	Social bonding	2.17	4.27
Applying feedback	1.88	3.33	Using resources	1.6	3.32
Organising	2.46	2.79	Writing arguments	4.22	5.88
Planning	0.12	0.47	Writing text	4.41	4.55

4.1. The structure of the self-regulation network

The psychological network of self-regulating behaviour shows that there is a strong correlation between *writing text* and *social bonding* as well as between *acknowledging* and *social bonding,* while there is only a weak correlation between *acknowledging* and *writing text* (Figure 1). By using the principles of the psychological network, this means there is a strong conditional dependence between *writing text* and *social bonding*, and between *social bonding* and *acknowledging* after taking into consideration all other variables in the network. We have also identified a strong conditional dependence between *writing arguments* and *reflecting*, between *writing arguments* and *acculturating*, between *organising* and *acculturating,* between *organising* and *acculturating*, and between *reflecting* and *applying feedback*. A moderate correlation was found between *writing arguments* and *using resources*, as well as between *using resources* and *acculturating*. Other notable results include observations such as the fact that *applying feedback* is only weakly connected to all other relevant tactics, except for *reflecting*, and that *planning* does not seem to have strong connections whatsoever.

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

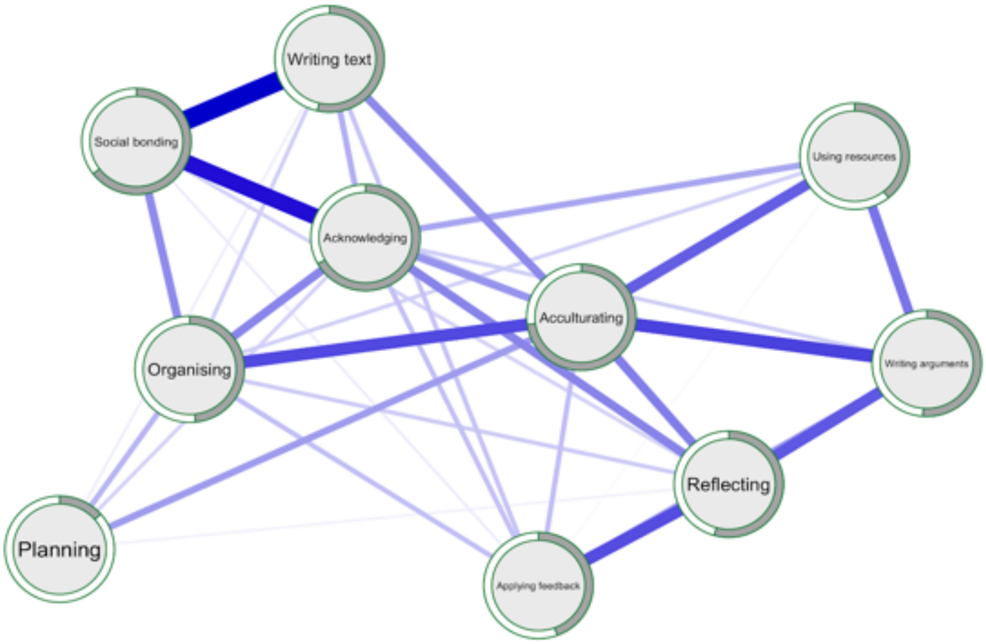

Figure 1: GGM network of self-regulation. Blue edges indicate positive partial correlations. Grey pie ring shows the proportion of explained variance (R1).

In Figure 1, we can observe the formation of three groups of strongly dependent and, therefore, connected behaviours: 1. a social group, comprised of *social bonding* and *acknowledging*, supplemented, in part, with *writing text* 2. a reflective group, comprised of *applying feedback* and *reflection*, and 3. a managing group, comprised of *acculturating*, *organising* and *using resources*, as well as *writing arguments*. The pie rings around each node show how much the node's connections explain its value. The value of the nodes *acculturating*, *social bonding* and *acknowledging*, for instance, can be largely explained by their connections. Most other tactics can be moderately explained by their connections while *planning* showed very low predictability in this regard.

Unlike traditional social networks, the absence of edges in psychological networks signify conditional independence. In the present data set, there are some tactics which act independently. *Organising*, for example, is independent from *writing arguments*, which is, more or less, to be expected. More surprising is the fact that *planning* is independent from *applying feedback*, *social bonding*, *using resources* and *writing arguments*. Similarly, *writing text* is independent from *reflecting*, *using resources* and *writing arguments*. The centrality measures (Table 2) offer another window into the interconnectivity of the different tactics in the self-regulated learning network. *Acculturating* and *acknowledging* were the most strongly connected tactics, followed by *social bonding* and *reflecting*. We see that *acculturating*, *acknowledging* and *social bonding* were the elements with the most expected influence on all other tactics.

Table 2
Centrality measures of both Grade_network (see next section) and SRL_network

Grade_network	SRL network

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

node	Strength	Expected Influence	node	Strength	Expected Influence
Acculturating	1.00	1.00	Acculturating	1.00	1.00
Acknowledging	0.78	0.78	Acknowledging	0.77	0.77
Applying feedback	0.40	0.40	Applying feedback	0.35	0.35
Organising	0.60	0.60	Organising	0.52	0.52
Planning	0.08	0.08	Planning	0.00	0.00
Reflecting	0.57	0.57	Reflecting	0.54	0.54
Social bonding	0.66	0.66	Social bonding	0.64	0.64
Using resources	0.28	0.28	Using resources	0.23	0.23
Writing arguments	0.51	0.51	Writing arguments	0.47	0.47
Writing text	0.56	0.56	Writing text	0.44	0.44
Grades	0.00	0.00		NA	NA

These results indicate, most notably, that students in our sample chose to discuss form-specific elements of their writing process separately from the content and argumentation of their essays. It can also be observed that making plans about which steps to take next does not naturally find its way into peer discussions here, which might indicate the need for SRL-specific training in similar CSCL settings in the future [13]. *Social bonding* seems to form a bridge between several key tactics in the present sample as it relates to both product-oriented tactics (such as *writing text*) and process-oriented tactics (such as *organising*) (cf. [7]). Similar observations can be made for *acculturating* as this tactic spans between product-oriented tactics (such as *writing arguments* and *using resources*) and process-oriented tactics (such as *organising* and *reflecting*). These observations provide empirical evidence of the importance of social, informal engagement, on the one hand, and academic acculturation on the other, in the development of SRL strategies in CSCL settings [33]. Based on centrality measures, encouraging such social behaviour may, in turn, boost interaction and collaboration in these online contexts.

4.2. Does academic achievement influence the structure of self-regulation network?

The addition of students' grades as a variable in the network allowed us to estimate the association between different SRL tactics after controlling for students' academic performance (Figure 2). This approach enabled us to investigate if the use of SRL tactics is dependent on academic performance or not.

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

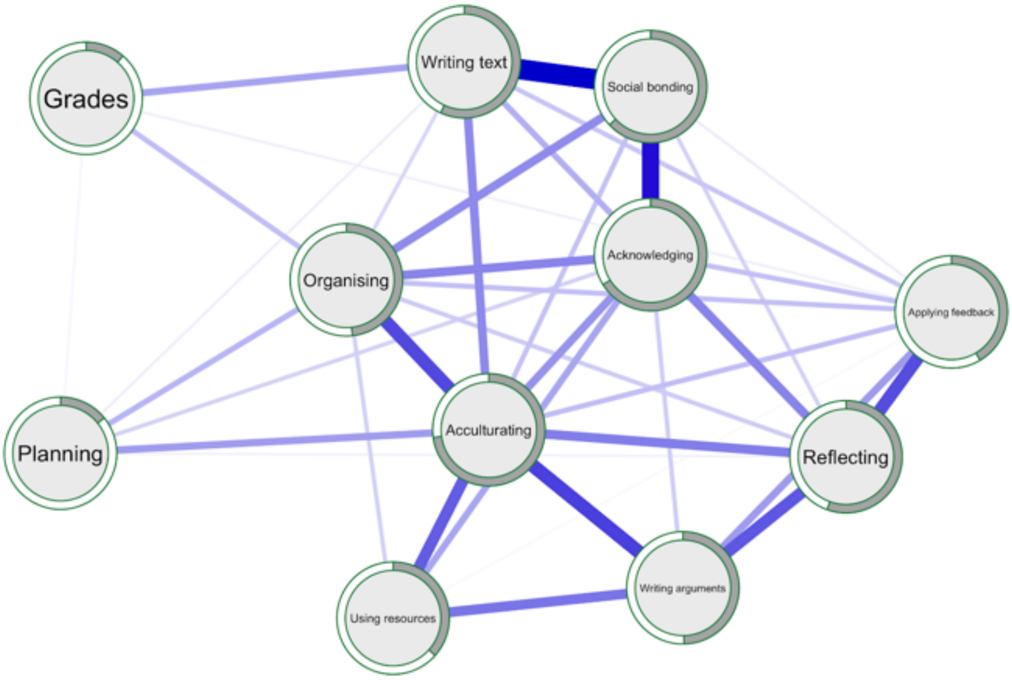

Figure 2: GGM network of self-regulation, after controlling for academic performance. Blue edges indicate positive partial correlations. Grey pie ring shows the proportion of explained variance (R2).

The structure of the Grade_network was fairly similar to the SRL_network where academic performance was not a variable, with some striking similarities (Table 3). First, we see strong connections between *writing text* and *social bonding*, and *social bonding* and *acknowledging* again. We also see similar trends for *acculturating*, *using resources*, *organising*, *reflecting* and *applying feedback*. Grades were only weakly correlated with *writing text*, *organising* and very weakly with *planning* and *applying feedback*. In other words, we can observe that a student's grade can hardly be explained by its connections to other variables. The centrality measures of strength and expected influence are also similar to the self-regulation network. These similarities indicate that students who score high marks in our sample may have similar approaches to language learning compared to students with lower marks, yet that they might apply tactics to a different degree. In other words, most students practice *writing text*, *social bonding* and *acknowledging* in their collaboration, but might do so more or less frequently, which might influence their academic success in the end.

Table 3

Variables and corresponding explained variance for Grade_network and SRL_network

Variable	Grade_network R2	SRL_network R2	Variable	Grade_network R2	SRL_network R2
Acculturating	0.583	0.583	Reflecting	0.492	0.493
Acknowledging	0.522	0.531	Social bonding	0.558	0.56
Applying feedback	0.383	0.393	Using resources	0.356	0.361
Organising	0.491	0.487	Writing arguments	0.449	0.455
Planning	0.151	0.139	Writing text	0.464	0.42
			Grades	0.159	NA

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

5. Conclusion: The added value of GGM

In accordance with the first research question, GGM has allowed us to model the complex interactions and dependencies among different SRL tactics using a robust estimation method which only takes into account relationships after controlling for all other variables in the network. This means that every visible link in the network is both significant, independent of collinearity with other variables and represents a substantial dependence or association between the nodes (in our case SRL tactics). GGM has also allowed us to verify the network model using simulation and bootstrapping. Furthermore, the conservative estimation approach (i.e., regularisation) helps discard insignificant relationships and prevents overfitting, making the graphs easier to read and interpret. The absence of edges in a GGM helps one understand the lack of dependence among nodes, which in other methods, cannot be accounted for. Additionally, the paths between nodes that a GMM can generate, help us understand the structure of a network and help generate a hypothesis about the structure of the studied phenomena.

Answering the second research question, we were able to observe that students' academic achievement does not immediately or inherently relate to students' approaches to self-regulated language learning in our sample. Other factors such as frequency of use and time spent on learning might be more influential in this regard, but this should be the subject of further research.

6. References

[1] Hamman, L. (2005). Self-regulation in academic writing tasks. *International Journal of Teaching and Learning in Higher Education, 17*(1), 15–26.

[2] Golombek, C., Klingsieck, K. B., & Scharlau, I. (2019). Assessing self-efficacy for self-regulation of academic writing: Development and validation of a scale. *European Journal of Psychological Assessment, 35*(5), 751–761. https://doi.org/10.1027/1015-5759/a000452

[3] Manso Vázquez, M., Caeiro, M. & Llamas Nistal, M. (2018). An xAPI Application Profile to Monitor Self-Regulated Learning Strategies. *IEEE Access. 6*. doi:10.1109/ACCESS.2018.2860519.

[4] Peeters, W., Saqr, M., & Viberg, O. (2020, *in press*). Applying learning analytics to map students' self-regulated learning tactics in an academic writing course. In H. J. So et al. (Eds.), *Proceedings of the 28th International Conference on Computers in Education.*

[5] Viberg, O., Khalil, M., & Baars, M. (2020). Self-regulated learning and learning analytics in online learning environments: a review of empirical research. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*, pp. 524–533, doi:10.1145/3375462.3375483

[6] Montrul, S. (2019). How learning context shapes heritage and Second Language Acquisition. In M. Dressman & W. Randall (Eds.), *The Handbook of Informal Language Learning* (pp. 57–74). Singapore: Wiley Blackwell.

[7] Peeters, W., & Ludwig, C. (2017). 'Old concepts in new spaces'? – A model for developing learner autonomy in social networking spaces. In T. Lewis, A. Rivens Mompean & M. Cappellini (Eds.), *Learner autonomy and Web 2.0* (pp. 117–142). Sheffield: Equinox.

[8] Peeters, W. (2019). The peer interaction process on Facebook: A social network analysis of learners' online conversations. *Education and Information Technologies, 24*(5), 3177–3204.

[9] Li, H., Flanagan, B., Konomi, S. I., & Ogata, H. (2018). Measuring behaviors and identifying indicators of self-regulation in computer-assisted language learning courses. *Research and Practice in Technology Enhanced Learning, 13*(1), 1–12. https://doi.org/10.1186/s41039-018-0087-78

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

[10] ElSayed, A. A., Caeiro-Rodríguez, M., MikicFonte, F. A., & Llamas-Nistal, M. (2019). Research in learning analytics and educational data mining to measure self-regulated learning: A systematic review. In *World Conference on Mobile and Contextual Learning* (pp. 46–53).

[11] Saint J., Gašević D., Pardo A. (2018). Detecting Learning Strategies Through Process Mining. In: V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink & M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning. EC-TEL 2018. Lecture Notes in Computer Science, vol 11082*. Springer, Cham. https://doi.org/10.1007/978-3-319-98572-5_29

[12] Ahmad Uzir, N. et al. (2019) Discovering time management strategies in learning processes using process mining techniques. In M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Ioannou & J. Schneider (Eds.), *Transforming learning with meaningful technologies. EC-TEL 2019. Lecture Notes in Computer Science, vol 11722*. Springer, Cham. https://doi.org/10.1007/978-3-030-29736-7_41

[13] Oxford, R. (2016). *Teaching and researching language learning strategies: Self-regulation in context*. Routledge.

[14] Borsboom, D., & Cramer, A. O. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology, 9*(1), 91–121. doi:10.1146/annurev-clinpsy-050212-185608

[15] Schmittmann, V. D., Cramer, A. O., Waldorp, L. J., Epskamp, S., Kievit, R. A., & Borsboom, D. (2013). Deconstructing the construct: A network perspective on psychological phenomena. *New ideas in psychology, 31*(1), 43–53.

[16] Epskamp, S., Waldorp, L. J., Mottus, R., & Borsboom, D. (2018). The Gaussian Graphical Model in cross-sectional and time-series data. *Multivariate Behavioral Research, 53*(4), 453–480.

[17] Robinaugh, D. J., Hoekstra, R. H., Toner, E. R., & Borsboom, D. (2020). The network approach to psychopathology: A review of the literature 2008–2018 and an agenda for future research. *Psychological Medicine, 50*(3), 353–366.

[18] Epskamp, S., Borsboom, D., & Fried, E. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods 50*, 195–212. doi:10.3758/s13428-017-0862-1

[19] Harris, K., Graham. S., Mason, L., & Saddler, B. (2002). Developing self-regulated writers. Theory into Practice, 41(2), 110-115.

[20] Zimmerman, B., & Risemberg, R. (1997). Becoming a self-regulated writer: A social cognitive perspective. *Contemporary Educational Psychology, 22*(1), 73–101.

[21] Teng, L. S., & Zhang, L. J. (2020). Empowering learners in the second/foreign language classroom: Can self-regulated learning strategies-based writing instruction make a difference? *Journal of Second Language Writing, 48*. https://doi.org/10.1016/j.jslw.2019.100701

[22] Yu, L. (2015). Effects of intervention on self-regulated learning for second language learners. *Doctoral thesis* http://scholarworks.uark.edu/etd/1229

[23] Dado, M., & Bodemer, D. (2017). A review of methodological applications of social network analysis in computer-supported collaborative learning. *Educational Research Review, 22*, 159–180. https://doi.org/10.1016/j.edurev.2017.08.005.

[24] Saqr, M., Fors, U., & Nouri, J. (2019). Time to focus on the temporal dimension of learning: a learning analytics study of the temporal patterns of students' interactions and self-regulation. *International Journal of Technology Enhanced Learning 11*, 398. https://doi.org/10.1504/ijtel.2019.10020597.

[25] Saqr, M., Viberg, O., & Vartiainen, H. (2020). Capturing the participation and social dimensions of computer-supported collaborative learning through social network analysis: Which method and measures matter? *International Journal of Computer Collaborated Learning 15*, 227–248. https://doi.org/10.1007/s11412-020-09322-6.

[26] Saqr, M., Nouri, J., Vartiainen, H., & Malmberg, J.: What makes an online problem-based group successful? A learning analytics study using social network analysis. *BMC Medical Education, 20*(80). https://doi.org/10.1186/s12909-020-01997-7

[27] Gašević, D., Joksimović, S., Eagan, B., & Shaffer, D. W. (2019). SENS: Network analytics to combine social and cognitive perspectives of collaborative learning. *Computers in Human Behavior, 92*, 562–577.

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.

EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774

[28] Rolim, V., Ferreira, R., Lins, R. D., & Gašević, D. (2019). A network-based analytic approach to uncovering the relationship between social and cognitive presences in communities of inquiry. *The Internet and Higher Education, 42*, 53–65.
[29] McClelland M. et al. (2018) Self-Regulation. In N. Halfon, C. Forrest, R. Lerner & E. Faustman (Eds.), *Handbook of Life Course Health Development* (pp. 275–298). Springer, Cham. https://doi.org/10.1007/978-3-319-47143-3_12
[30] Reed, R., Combs, H, & Segerstrom, S. (2020). The Structure of self-regulation and its psychological and physical health correlates in older adults. *Collabra: Psychology, 6*(1), 23. http://doi.org/10.1525/collabra.297
[31] Farina, M. (2018). *Facebook and conversation analysis*. London, Bloomsbury.
[32] Tibshirani, R. (1996). Regression shrinkage and selection via the LASSO. *Journal of the Royal Statistical Society, Series (B), 58*(1), 267–288.
[33] Sockett, G., & Toffoli, D. (2019). Last words: Naming, framing, and challenging the field. In M. Dressman & W. Randall (Eds.), *The Handbook of Informal Language Learning* (pp. 471–487). Singapore: Wiley Blackwell.

Harnessing the Potentials of Technology to Support Self-Directed Language Learning in Online Learning Settings, October 15–16, 2020, Stockholm, Sweden and Chiba, Japan.
EMAIL: mmas@kth.se; oviberg@kth.se; peeters-w@kanda.kuis.ac.jp
ORCID: 0000-0001-5881-3109; 0000-0002-8543-3774