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Enhancing Learner Models for Pedagogical Agent Scaffolding of Self-Regulated Learning

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Abstract: Self-regulated learning (SRL) processes for monitoring and modulating one's own cognition, affect, metacognition, and motivation are essential for effective learning within intelligent tutoring systems (ITSs). As such, pedagogical agents are typically embedded within these environments to scaffold learners' SRL via prompts to engage in these processes. However, current pedagogical agents follow pre-established, production rules based on temporal and frequency inputs from the learner which limits the ability for these agents to provide individualized scaffolding intelligently and adaptively. In this paper, we argue that this issue originates from an underdeveloped learner model that does not comprehensively track the dynamic nature of SRL. This paper introduces recurrence plots, which visualize system dynamics, as a novel method for enhancing learner models to provide pedagogical agents the information necessary to interpret the dynamics of learners' enacted SRL processes captured using log files as they engaged with instructional materials during learning with an ITS. In merging recurrence plots and the field of SRL, learner models can be enhanced with information regarding learners' dynamical use of SRL processes to augment the accuracy and sophistication of pedagogical agent scaffolding.

Keywords: Pedagogical agent, self-regulated learning, recurrence plot, scaffolding

1. Introduction and Related Work on Pedagogical Agents and ITSs

Proficient learners can autonomously engage with instructional materials by deploying self-regulated learning (SRL) processes such as defining tasks, using cognitive and metacognitive SRL strategies during the learning task, reflecting on their progress, identifying goals, setting plans to achieve those goals, and modifying goals, plans, and strategies (Poitras & Lajoie, 2014; Winne, 2018). SRL processes are essential for effective learning of complex topics and are especially critical for environments that are open-ended and do not provide instructional scaffolding (Azevedo et al., 2022). However, learners are typically unable to demonstrate accurate and effective deployment of SRL processes during learning, possibly due to lack of metacognitive knowledge, thereby resulting in increased cognitive load and decreased learning gains (Azevedo et al., 2018; Josephsen, 2017; Paans et al., 2019; Taub & Azevedo, 2019). Because of this, advanced learning environments, such as intelligent tutoring systems (ITSs), provide instructional scaffolds in the form of pedagogical agents to detect, track, and foster learners' SRL processes. We argue that the accuracy and sophistication of pedagogical agents' individualized scaffolding and feedback can be significantly enhanced through visualizing and quantifying recurrence based on individual learners' enactment of SRL processes.

In a systematic literature review by Martha and Santoso (2019), pedagogical agents within ITSs were touted as useful for increasing domain knowledge and changing learner behavior, including SRL strategies and affect, through hinting, prompting, and providing feedback to learners. However, most pedagogical agents integrated with ITSs are rigidly programmed to follow a linear set of production rules based on temporal and frequency inputs (Webber & Marwan, 2015). In consequence, pedagogical agents do not monitor the degree to which learners' deployment of SRL strategies demonstrates a dynamical relationship and thus does not intervene to scaffold functional SRL processes. This paper sets a rationale for using a nonlinear dynamical systems theory tool to detect, quantify, and visualize learners' changes and transitions of SRL behavior. In proposing this novel technique, this paper provides groundwork for pedagogical agents as interpreters of complex learner visualizations to scaffold SRL during learning with an ITS.

ITSs are computerized instructional systems containing multimodal materials (e.g., video, text, diagram) that provide real-time adaptive instruction to learners (Graesser et al., 2018). ITSs embed a level of intelligence dispersed between several models including a knowledge or expert model, learner model containing information about how the learner exhibits learning behaviors, pedagogical model containing the different strategies of tutoring or teaching, and interface or communication model (Sottilare et al., 2018). ITSs include a level of adaptivity which allows for information obtained from an evolving learner model to be compared against pre-determined desired behaviors for identification of discrepancies between learner and expert models (Mousavinasab et al., 2018). Learner models are comparable to the concept of physical DNA such that these models track and store qualitative and quantitative information representing learner characteristics and knowledge (Akkila et al., 2019). Consequentially, learner models must constantly self-update information due to the dynamic nature of learner behavior, i.e., changing over time, and interaction as learners' new knowledge emerges, relationships between concepts are made, and SRL skills are developed. These learner models are the foundation for the adaptivity displayed within effective ITSs that can emulate and simulate human tutor behaviors in providing individualized tutoring in the form of prompts and feedback to a learner via pedagogical agents (Kim & Baylor, 2016; Johnson & Lester, 2018).

Pedagogical agents are artificially intelligent virtual characters within ITSs that provide some level of instructional, cognitive, or affective support, simulating and mimicking physical tutor-learner interactions (Hooshyar et al., 2015; Johnson & Lester, 2018). Several ITSs throughout education literature have used pedagogical agents to provide information to the learner, prompt the learner to engage in learning or SRL processes, monitor learners' interactions, and provide just-in-time feedback to scaffold learning with an ITS (Velestianos & Russell, 2014). One notable example of an ITS is MetaTutor, a hypermedia based ITS for improving knowledge about the human circulatory system (see Azevedo et al., 2022). This ITS contains several pedagogical agents that prompt learners to engage in different SRL processes. The way in which the pedagogical agents of MetaTutor interact and dialogue with learners is grounded in a series of production rules that are both time- and frequency-based. For example, if a learner has not deployed a content evaluation after a certain number of minutes, a pedagogical agent prompts the learner to engage in this strategy via dialogue. The logic behind the artificially intelligent decisions made by pedagogical agents throughout ITSs to intervene, foster, or prompt learners to engage in certain behaviors during learning most commonly use action-condition rule-based reasoning (Mousavinasab et al., 2018). However, a few limitations of pedagogical agents arise regarding: (1) the extent to which pedagogical agents can be considered beneficial for learning; and (2) the "intelligence" of the pedagogical agents in their adaptive capabilities.

2. Limitations of Pedagogical Agents

While the benefits of pedagogical agents have been extensively researched within educational literature for the support of learning and cognitive processes (Azevedo et al., 2016, 2018; Castro-Alonso et al., 2021; Hidayah et al., 2019), studies have not conclusively identified the effectiveness of pedagogical agents. While some studies support the need for pedagogical agents as scaffolders of learning outcomes (Bouchet et al., 2016; Davis, 2018; Dever et al., 2022; Harley et al., 2017; Schroeder et al., 2013; Wiedbusch et al., 2021), other studies conclude that pedagogical agents do not significantly contribute to greater learning outcomes or increased use of SRL processes (Castro-Alonso et al., 2021; Schroeder et al., 2017; Yilmaz & Yilmaz, 2020). The current paper argues that the lack of cohesive findings regarding the usefulness of pedagogical agents as scaffolds for SRL stem from underdeveloped learner models used by pedagogical agents for detecting, tracking, analyzing, and responding to learners' deployment of SRL strategies while learning with an ITS.

While ITSs are intended to provide instructional tutoring and personalization as learners engage with materials throughout the environment and deploy SRL processes (Hooshyar et al., 2015), pedagogical agents currently do not demonstrate intelligent behaviors needed to provide effective, timely, and adaptive individualized scaffolding for significantly increasing learning outcomes (SchezSobrino et al., 2020). As learner behavior is dynamic, i.e., changing over time, developing an ITS which intelligently and constantly updates learner models and provides adaptive instructional feedback is difficult to achieve (Bouchet et al., 2016; Holstein et al., 2018). The majority of ITSs employ pedagogical agents that interact with the learner model on a predetermined set of actions and rules which assumes that the conditions for a specific prompt are uniform across all learners regardless of SRL skills, metacognitive knowledge, domain understanding, motivation, demographics, etc. This limits the intelligence of systems and defies the dynamic, nonlinear nature of SRL.

To counteract these limitations of pedagogical agents, a new approach to informing and updating learner models that acknowledges the nonlinear dynamics of SRL processes and both qualitatively and quantitatively informs pedagogical agents embedded in ITSs is required (e.g., Li et. al., 2022). We outline and demonstrate a new statistical and visual technique in the field of SRL and ITSs that allows for the evaluation of dynamically changing SRL behaviors to be more accurately and comprehensively updated in learner models to improve how and when pedagogical agents prompt learners to engage in SRL processes during learning.

3. Recurrence Plots as Visualizations of SRL Behavior

Complexity science incorporates nonlinear dynamical systems theory (NDST) which states that small changes in behavior can have a large, nonlinear shift in future behavior (Amon et al., 2019). Recurrence Quantification Analysis (RQA) is an NDST analytical technique for measuring and visualizing the degree to which complex systems, or SRL behavior in our paper, demonstrate chaotic and stable patterns of behavior over time (Vrzakova et al., 2019). Recurrence plots are graphical visualizations of couplings between system components across all time points within each component's time series that can reveal the changes and transitions in system dynamics (Webber & Marwan, 2015). In other words, a recurrence plot identifies each time at which a specific state recurs between two time-identical (i.e., auto-RQA) or time-different (i.e., cross-RQA, multidimensional-RQA) time series. Within this paper, we describe categorical auto-RQA (i.e., aRQA; see Dale & Spivey, 2005) recurrence and provide a preliminary example of how these visualizations can be used to describe SRL in ITSs.

Recurrence plots are structured in a two-dimensional matrix format with the time series on both the X and Y axes. At the intersection of the X and Y axis within the matrix, a solid black dot is placed should the SRL behavior the learner engages in on the X axis recur with the SRL behavior on the Y axis whereas intersections where behaviors do not recur are kept white (Zou et al., 2019). The plot holds a solid black diagonal line from the bottom left of the plot to the top right called the line of identity. The line of identity represents the time at which the time series recurs with itself where Time 1 on the X axis is compared with Time 1 on the Y axis. While the researcher should be aware of this line, the recurrence of a state is not of interest when it recurs with itself as it does not reveal relationships across time (Webber & Marwan, 2015). It is important to note that a recurrence indicator at time intersection (i, j) does not contain information that can be generalized throughout the entire system across time; rather, it is the culmination of all recurrence points that produce interpretable structural patterns that should be considered to diagnose the dynamics of a system. The structure of recurrent points across the plot can indicate if the overall processes of a system are stationary, nonstationary, cyclic, deterministic (i.e., stable), or chaotic. For example, should there be several long diagonal lines that are parallel to the line of identity on a recurrence plot, the system can be described as more deterministic than a recurrence plot displaying several shorter diagonals (Webber & Marwan, 2015). Stationary systems are visualized by the equal dispersion of recurring patterns across a plot whereas nonstationary systems display fading or darkening areas within the recurrence plot (Webber & Marwan, 2015).

While studies across various disciplines (e.g., Sujith & Unni, 2021; Vrzakova et al., 2019) have utilized recurrence plots to visualize complex systems, very few studies have examined how recurrence plots can visualize learner interactions with an ITS (see Allen et al., 2017; Li et al., 2022). Several advantages exist in utilizing recurrence plots to drive pedagogical agents' instructional interventions as learners engage with materials throughout an ITS. First, several types of data can be applied to this statistical technique. This includes both categorical and continuous data that is outputted from data sources including log files, eye tracking, concurrent verbalizations, written answers, etc. As such, recurrence plots can be used across a variety of contexts and domains while adhering to restrictions that may occur in natural environments (e.g., log files collected in classrooms; Dale & Spivey, 2005). Second, recurrence plots can exist in parallel with noisy, unstructured environments that typically contest the assumptions of typically powerful linear analytical tools (Vrzakova et al., 2019; Webber & Marwan, 2015). As SRL processes are complex systems, the method in which learners deploy SRL should be analyzed and interpreted as such. In using RQA and recurrence plots as visualizations of SRL processes researchers, and by extension pedagogical agents in ITSs, can methodologically and analytically respect the complexity of SRL. Finally, recurrence plots can be utilized to both qualitatively *and* quantitatively examine the characteristics of learners' SRL. In addition to the qualitative topographies and patterns that can be extracted from recurrence plot visualizations to provide information as to the temporal dynamics of a system, quantitative statistical measures can be extracted from the organization and frequency of the black indicators of recurrent patterns. These metrics extracted from recurrence plots have the potential for describing learners' SRL without diluting the rich data that can be extracted from their interactions with the ITS (Li et al., 2022). At the crux of these advantages exists the question of how recurrence plots can be used by ITSs to update the learner model to improve pedagogical agent scaffolding of SRL.

For this paper, we extracted a representative participant from a sample of undergraduate students who learned about the human circulatory system with an ITS, MetaTutor, while receiving prompts from pedagogical agents to deploy SRL strategies. The participant extracted had a minimum of ten SRL events and demonstrated the lowest learning gains out of the entire sample of participants receiving scaffolding. This participant's recurrence plot over time visually displays a noticeable shift in the recurrence of deployed SRL strategies. Specifically, the participant shifts from displaying functional SRL behaviors (Figure 1A.) to dysfunctional (Figure 1B.). While towards the end of their session the participant displays functional SRL behaviors (Figure 1C.), the participant was unable to recover as exhibited by their low learning gains. The method in which this participant's data was extracted and visually examined serves as the first exploration into interpreting visualizations of the dynamics of learners' SRL use to transform the traditional learner model and enhance pedagogical agent scaffolding.

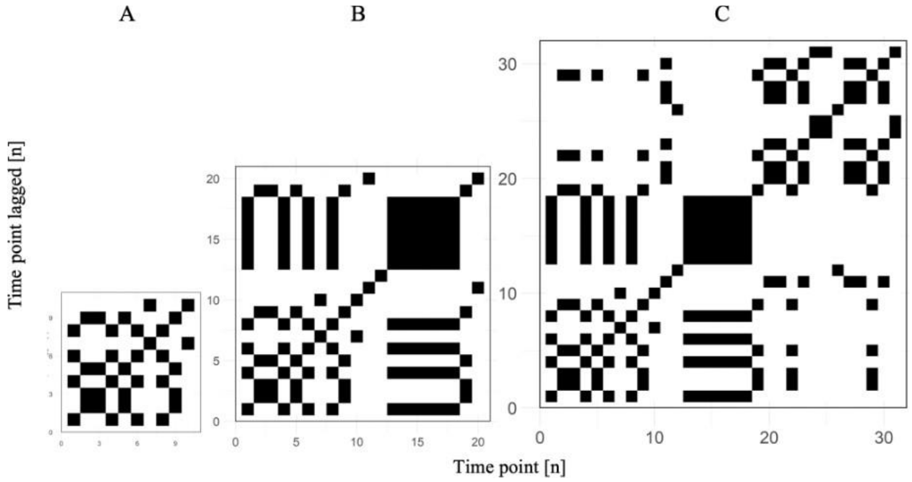

Figure 1. Recurrence plot changing over time as learners engage in SRL processes.

4. Future Directions in Pedagogical Agent Research and Development

The use of recurrence plots, specifically their interpretation, within SRL and ITS research will vary depending on the learning outcomes, measures, and processes of interest. Past studies have found mixed findings regarding what constitutes as "desirable" SRL behaviors exhibited by students. Dever et al. (2022) found that a recurrence plot with a homogeneous distribution of recurrent and nonrecurrent patterns of SRL behaviors scaffolded by pedagogical agents during learning about the human circulatory system are indicative of healthy deployment of SRL strategies. Meanwhile, more recurrent behaviors in the study by Li et al. (2022) described in the previous section are indicators of high performance while diagnosing a virtual patient. In consequence, future directions in research should research and understand the balance needed between chaotic and stable states to produce greater learning outcomes. From this, researchers will be better able to inform how and when pedagogical agents should intervene to provide scaffolding to learners while deploying SRL processes in an ITS.

Merging recurrence plots from RQA and the field of SRL will allow learner models to be updated with information regarding the functional use of SRL processes as learners engage with instructional materials within an ITS. By updating learner models with this type of information and data only accessible through RQA (and by extension recurrence plots) pedagogical agents would be able to identify a correct point in time in which to provide scaffolding to learners. As recurrence plots divulge information about the dynamics of a complex system, future pedagogical agents can provide scaffolding that is more geared towards fostering functional dynamics rather than depending on temporal and frequency data pervading learner models today.

References

Akkila, A. N., Almasri, A., Ahmed, A., Al-Masri, N., Sultan, Y. A., Mahmoud, A. Y., ... & Abu-Naser, S. S. (2019). Survey of Intelligent Tutoring Systems up to the end of 2017. *International Journal of Academic Information Systems Research (IJAISR)*, *3*(4).

Allen, L. K., Perret, C., Likens, A., & McNamara, D. S. (2017, March). What'd you say again? Recurrence quantification analysis as a method for analyzing the dynamics of discourse in a reading strategy tutor. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 373-382).

Amon, M. J., Vrzakova, H., & D'Mello, S. K. (2019). Beyond dyadic coordination: Multimodal behavioral irregularity in triads predicts facets of collaborative problem solving. *Cognitive Science, 43,* e12787.

Azevedo, R., Martin, S.A., Taub, M., Mudrick, N.V., Millar, G.C., Grafsgaard, J.F. (2016). Are pedagogical agents' external regulation effective in fostering learning with intelligent tutoring systems? In A. Micarelli, J. Stamper, & K. Panourgia (Eds.), *Lecture Notes in Computer Science*, Vol. 9684, *International Conference on Intelligent Tutoring Systems* (pp. 197-207). Springer.

Azevedo, R., Taub, M., Mudrick, N.V. (2018). Understanding and reasoning about real-time cognitive, affective, and metacognitive processes to foster self-regulation with advanced learning technologies. In P. A. Alexander, D. H. Schunk, & J. A. Greene (Eds.) Handbook of Self-regulation of Learning and Performance (2nd ed., pp. 254–270). Routledge. https://doi.org/10.4324/9781315697048

Azevedo, R., Bouchet, F., Duffy, M., Harley, J., Taub, M., Trevors, G., Cloude, E., Dever, D., Wiedbusch, M., & Wortha, F. (2022). Lessons learned and future directions of MetaTutor: Leveraging multichannel data to scaffold self-regulated learning with an intelligent tutoring system. *Frontiers in Psychology.* doi: 10.3389/fpsyg.2022.813632

Bouchet, F., Harley, J. M., & Azevedo, R. (2016, June). Can adaptive pedagogical agents' prompting strategies improve students' learning and self-regulation?. In *International conference on intelligent tutoring systems* (pp. 368-374). Springer, Cham.

Castro-Alonso, J. C., Wong, R. M., Adesope, O. O., & Paas, F. (2021). Effectiveness of multimedia pedagogical agents predicted by diverse theories: A meta-analysis. *Educational Psychology Review*, 33, 989-1015.

Dale, R., & Spivey, M. J. (2005). Categorical recurrence analysis of child language. In *Proceedings of the 27th Annual Meeting of the Cognitive Science Society* (pp. 530-535). Mahwah, NJ: Lawrence Erlbaum.

Davis, R. O. (2018). The impact of pedagogical agent gesturing in multimedia learning environments: A meta-analysis. *Educational Research Review, 24,* 193-209.

Dever, D. A., Sonnenfeld, N., Wiedbusch, M. D., & Azevedo, R. (2022, July). Pedagogical agency support and its relationship to learners' self-regulated learning strategy use. In M. M. Rodrigo, N. Matsuda, A. I. Cristea, & V. Dimitrova (Eds.), *Proceedings of the 23rd International Conference of Artificial Intelligence in Education,* (pp. 332-343). Springer.

Graesser, A. C., Hu, X., & Sottilare, R. (2018). *Intelligent tutoring systems.* In F. Fischer, C. Hmelo-Silver, S. Goldman, & P. Reimann (Eds.), *International handbook of the learning sciences* (pp. 246-255). New York: Routledge.

Harley, J. M., Taub, M., Azevedo, R., & Bouchet, F. (2017). Let's set up some subgoals: Understanding human-pedagogical agent collaborations and their implications for learning and prompt and feedback compliance. *IEEE Transactions on Learning Technologies*, *11*, 54-66.

Hidayah, I., Adji, T. B., & Setiawan, N. A. (2019). Development and evaluation of adaptive metacognitive scaffolding for algorithm-learning system. *IET Software*, 13, 305-312.

Holstein, K., Yu, Z., Sewall, J., Popescu, O., McLaren, B. M., & Aleven, V. (2018, June). Opening up an intelligent tutoring system development environment for extensible student modeling. In *International conference on artificial intelligence in education* (pp. 169-183). Springer, Cham.

Hooshyar, D., Ahmad, R. B., Yousefi, M., Yusop, F. D., & Horng, S. J. (2015). A flowchart-based intelligent tutoring system for improving problem-solving skills of novice programmers. *Journal of Computer Assisted Learning*, *31*(4), 345-361.

Johnson, W. L., & Lester, J. C. (2018). Pedagogical agents: back to the future. *AI Magazine, 39*, 33-44.

Josephsen, J. M. (2017). A qualitative analysis of metacognition in simulation. Journal of Nursing Education, 56, 675-678.

Kim, Y., & Baylor, A. L. (2016). Research-based design of pedagogical agent roles: A review, progress, and recommendations. *International Journal of Artificial Intelligence in Education*, *26*, 160-169.

Li, S., Zheng, J., & Lajoie, S. P. (2022). Temporal Structures and Sequential Patterns of Self-regulated Learning Behaviors in Problem Solving with an Intelligent Tutoring System. *Educational Technology & Society*, *25*(4), 1-14.

Martha, A. S. D., & Santoso, H. B. (2019). The design and impact of the pedagogical agent: A systematic literature review. *Journal of Educators Online*, *16*(1), n1.

Mousavinasab, E., Zarifsanaiey, N., R. Niakan Kalhori, S., Rakhshan, M., Keikha, L., & Ghazi Saeedi, M. (2018). Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods. *Interactive Learning Environments*, 1-22. doi:10.1080/10494820.2018.1558257

Paans, C., Molenaar, I., Segers, E., & Verhoeven, L. (2019). Temporal variation in children's self-regulated hypermedia learning. *Computers in Human Behavior*, *96*, 246-258.

Poitras, E. G., & Lajoie, S. P. (2014). Developing an agent-based adaptive system for scaffolding self-regulated inquiry learning in history education. *Educational Technology Research and Development*, *62*(3), 335-366.

Schez-Sobrino, A., Gmez-Portes, C., Vallejo, D., Glez-Morcillo, C., & Redondo, M. Á. (2020). An intelligent tutoring system to facilitate the learning of programming through the usage of dynamic graphic visualizations. *Applied Sciences, 10.* doi: :10.3390/app10041518.

Schroeder, N. L., Adesope, O. O., & Gilbert, R. B. (2013). How effective are pedagogical agents for learning? A meta-analytic review. *Journal of Educational Computing Research*, 49, 1-39.

Schroeder, N. L., Romine, W. L., & Craig, S. D. (2017). Measuring pedagogical agent persona and the influence of agent persona on learning. *Computers & Education*, 109, 176-186.

Sottilare, R. A., Graesser, A. C., Hu, X., & Sinatra, A. M. (Eds.). (2018). *Design recommendations for intelligent tutoring systems: Team tutoring* (vol. 6). US Army Research Laboratory.

Sujith, R. I., & Unni, V. R. (2021). Dynamical systems and complex systems theory to study unsteady combustion. *Proceedings of the Combustion Institute*, *38*(3), 3445-3462.

Taub, M., & Azevedo, R. (2019). How does prior knowledge influence eye fixations and sequences of cognitive and metacognitive SRL processes during learning with an Intelligent Tutoring System? *International Journal of Artificial Intelligence in Education*, *29*(1), 1-28.

Veletsianos, G., & Russell, G. S. (2014). Pedagogical agents. In *Handbook of research on educational communications and technology* (pp. 759-769). Springer, New York, NY.

Vrzakova, H., Amon, M. J., Stewart, A. E., & D'Mello, S. K. (2019, May). Dynamics of visual attention in multiparty collaborative problem solving using multidimensional recurrence quantification analysis. In *Proceedings of the 2019 CHI conference on human factors in computing systems* (pp. 1-14).

Webber, C. L., & Marwan, N. (2015). Recurrence quantification analysis. *Theory and Best Practices*. - Mathematical and computational foundations of recurrence quantifications

Wiedbusch, M., Dever, D., Wortha, F., Cloude, E.B., & Azevedo, R. (2021). Revealing data feature differences between system- and learner-initiated self-regulated learning processes within hypermedia. In R. A. Sottilare, & J.Schwarz (Eds.), *Lecture Notes in Computer Science*, Vol. 12792, *Adaptive Instructional Systems. Design and Evaluation*. Springer. https://doi.org/10.1007/978-3-030-77857-6_34

Winne, P. H. (2018). Theorizing and researching levels of processing in self-regulated learning. *British Journal of Educational Psychology*, *88*(1), 9-20.

Yilmaz, R., & Karaoglan Yilmaz, F. G. (2020). Examination of the effectiveness of the task and group awareness support system used for computer-supported collaborative learning. *Educational Technology Research and Development*, *68*, 1355-1380.

Zou, Y., Donner, R. V., Marwan, N., Donges, J. F., & Kurths, J. (2019). Complex network approaches to nonlinear time series analysis. *Physics Reports*, *787*, 1-97.