



“We’re looking good”: Social exchange and regulation temporality in collaborative design

Ha Nguyen^{a,*}, Kyu Yon Lim^b, Liang Li Wu^c, Christian Fischer^d, Mark Warschauer^a

^a School of Education, University of California-Irvine, 3200 Education Bld, Irvine, CA, 92697, United States

^b Ewha Womans University, Republic of Korea, 52 Ewhayeodae-gil, Daehyeon-dong, Seodaemun-gu, Republic of Korea

^c The Henry Samueli School of Engineering, 1084 Anteater Instruction & Research Building (AIRB), University of California-Irvine, Irvine, CA, 92697, United States

^d Eberhard Karls University of Tübingen, Hector Research Institute of Education Sciences and Psychology, Euroastr. 6, Room, 404, 72072, Tübingen, Germany

ARTICLE INFO

Keywords:

Regulation
Project-based learning
Process mining
Network analysis
Discourse analysis

ABSTRACT

Collaborative tasks do not always promote equal learning. Varying levels of social interactions and regulation at the individual and group levels can influence knowledge construction efforts and learning success. To understand which collaboration patterns may be more conducive to learning, this study examined the relation between social exchange, regulation, and learning outcomes. Four project-based engineering undergraduate teams were audiotaped in collaborative tasks (7514 talk turns). Discourse was coded for regulation processes and types (self and socially shared regulation), and analyzed with Epistemic Network Analysis and Process Mining. We find that teams who reported more frequent social exchange engaged in shared regulation together with planning and monitoring more frequently, while teams with less exchange engaged in long durations of collaboration. Furthermore, students in teams with more engaged regulation reported enhanced beliefs in group efficacy to solve collaborative tasks. The study illustrates the potential of applying quantitative approaches to analyzing rich discourse.

1. Introduction

Collaborative project-based engineering has shown promise in integrating knowledge, practice, and group work to address complex design tasks (Mills & Treagust, 2003). Broadening collaboration opportunities for engineering undergraduates, especially among underrepresented minority and female students, can address the low retention and performance of underrepresented students in engineering and science (Allen-Ramdiel & Campbell, 2014).

Collaboration, however, does not always promote equal learning opportunities (Cohen & Lotan, 2014; Tonso, 2006). Students who are more involved in course-related social exchange may more actively seek resources and engage in knowledge construction (Dawson, 2008; Putnik et al., 2016). Students with more social exchange may also show higher commitment to group-level regulation: In collaborative learning, students not only regulate their own goals, affects, and behaviors (i.e., self-regulation), but also interact to regulate the group’s goals, emotions, and strategies towards task completion (i.e., socially shared regulation; Hadwin, Järvelä, & Miller, 2011). Thus, exploring how students with different frequencies of social exchange engage in self- and

shared regulation can help develop instructional scaffolds that foster adaptive learning strategies, a task that most learners find challenging (Järvelä & Hadwin, 2013).

Beyond frequencies of social exchange and regulation, the timing of regulation may also reflect the quality of collaborative learning (Banner, Reimann, & Sonnenberg, 2014; Järvelä, Malmberg, & Koivuniemi, 2016; Malmberg, Järvelä, & Järvenoja, 2017). Temporality can be examined as timing (i.e., when events occur), co-occurrence (i.e., when two events or event types occur), and sequence (i.e., order of events). However, these temporality aspects—timing, co-occurrence, and sequence—have rarely been examined in tandem. Exploring the nuances in temporality provides important insights into variation in student engagement and information acquisition (Hadwin, 2019). Our study attempts to contribute to this research.

In the following study, we examine the co-occurrences and sequential nature of regulation types and processes, in connection with perceived social exchange and learning outcomes. We selected an undergraduate project-based engineering course as the study setting for policy-relevant and theoretical insights. From a policy perspective, broadening collaborative learning for engineering undergraduates

* Corresponding author. 3200 Education Bld, Irvine, CA, 92697, United States.
E-mail address: thcn@uci.edu (H. Nguyen).

remains a challenge (Tonso, 2006). From a theoretical standpoint, project-based engineering provides ample opportunities for self- and shared regulation of planning, execution, and evaluation in iterative design cycles.

Our study bridges the gap between project-based engineering and regulation research in two main ways. First, project-based engineering research has mostly focused on self-regulation, rather than socially shared regulation (Galand, Raucent, & Frenay, 2010; Stefanou, Stolk, Prince, Chen, & Lord, 2013). We examine both self- and shared regulation processes. Second, project-based engineering researchers have primarily utilized surveys or interviews, instead of conversational data that illuminate the temporality of regulation (Galand et al., 2010; for exception, see; Purzer, 2011). We address these gaps by analyzing student discourse with temporal analyses, namely Epistemic Network Analysis (Shaffer, Collier, & Ruis, 2016) and Process Mining (Janssenswillen, Depaire, Swennen, Jans, & Vanhoof, 2019).

2. Theoretical framework

2.1. Regulation in collaboration

Regulation of learning describes learners' active control of cognition, motivation, and behavior towards learning goals (Zimmerman & Schunk, 2011). Effective self-regulated learners constructively set goals and then monitor their strategies, progress, and information given the goals and changing demands from learning environments (Pintrich, 2000). In addition to self-regulation, there is emergent interest in examining group-level goals and regulation in collaborative learning (Hadwin et al., 2011; Järvelä et al., 2015; Malmberg et al., 2017). Collaborative environments can facilitate the development of both personal and group goals. Group members may systematically self-regulate: activate and monitor their own goals. They may co-regulate: coordinate self-regulatory processes towards individual learner's goals, without co-constructing goals as a group (Hadwin et al., 2011; Miller & Hadwin, 2015). Members may also engage in socially shared regulation: co-construct goals and activities towards shared outcomes (Hadwin et al., 2011). Successful teams contain learners who can self-regulate, while guiding others' regulation and supporting shared regulation (Hadwin et al., 2011).

Models of self-regulated learning are typically grounded in a social cognitive perspective that considers learners' cognitive behaviors in social interactions. This grounding presents unique conceptual and methodological challenges. The first challenge pertains to capturing how learners iterate through regulation phases—timing, co-occurrences, and sequence (Hadwin, 2019; Järvelä, Järvenoja, & Malmberg, 2019). In the following sections, we review prior work that captures the timing and cyclical nature of regulation processes. The second challenge involves the need to document the interactions between tasks, group exchange, and learner past experiences that may influence the development of regulation and learning outcomes (Järvenoja, Järvelä, & Malmberg, 2015). Our framework situates aspects of regulation in a specific learning context (project-based engineering). We account for the role of social agents in regulation processes (Zimmerman, 2000) by reviewing how regulation can be linked to social exchange. Finally, we review the link between successful learning and regulation strategies that adapt to learning environments.

2.2. Regulation as cyclical process

Models of self-regulated learning often define regulation not as a unique state, but as context-specific processes that cycle through forethought, performance, and reflection (Zimmerman, 2000). In the forethought phase, learners analyze the tasks to assess their capacity for success, establish goals, and set plans. During performance, learners observe and control their behaviors, motivation, and emotions to maintain or adjust performance. Finally, during self-reflection, learners

evaluate their work and attribute reasons for their success or failure. These attributions in turn trigger emotions that affect the expectations and motivation for future tasks. Similar to self-regulated learning models, group-level regulation has also been defined as a process model that generally contains task understanding, goal setting and planning, execution, and evaluation (Hadwin et al., 2011; Malmberg et al., 2017). The transition between processes depends on the iterative monitoring of task understanding, goals, and strategies among group members, particularly when learning does not proceed as planned (Järvelä et al., 2015).

In conceptualizing regulation as a cyclical model, researchers have focused on specific processes that prompt individuals to initiate and maintain cognitive, behavioral, and affective engagement during learning (Zimmerman, 2000). Highly self-regulated learners may actively engage in all phases, not only setting goals and planning prior to learning, but also demonstrating self-control to optimize their focus on task and track performance over time (Zimmerman, 2000). Furthermore, the phases that learners engage in may vary with contexts (individual or group work) and regulation types (self-regulate, co-regulate, or shared regulation; Järvelä et al., 2019). Thus, mapping regulation processes to types can advance understanding of the roles of self- and group-level regulation processes in learning (Hadwin, 2019). For example, Malmberg et al. (2017) examined pre-service teachers' collaboration in a math course and found that shared regulation discourse mostly consists of task implementation, as opposed to forethought or evaluation. Besides Malmberg et al. (2017), however, few studies have examined how individuals cycle through self- and shared regulation phases during collaborative tasks.

Researchers have also attended to the sequence of regulated learning, building on the assumption that regulation of task understanding, goal setting, execution, and evaluation depends on the stage of learning (Bannert et al., 2014; De Backer, Van Keer, & Valcke, 2015; Järvelä et al., 2015; Molenaar & Chiu, 2014). Regulation processes are cyclical in that insights from evaluation can initiate another cycle of task perception, planning, and execution (Järvelä et al., 2015). The transition between regulation phases is related to learners' cognitive and social stages. Molenaar and Chiu (2014), for example, found that planning or evaluation activities fostered subsequent cognitive engagement, while monitoring activities helped groups focus on task. Bannert et al. (2014) illustrated the use of process mining to examine the sequence of activities in think-aloud tasks: Successful students looped between monitoring, reading information, and elaboration, whereas less successful students mainly read and repeated the task information. Together, prior work illustrates the need to examine regulation not as a static state, but as a process model that aligns with regulation types and stage of learning, both of which are grounded in learning contexts.

2.3. Regulation in collaborative project-based engineering contexts

One way to study regulation in situ is to articulate which aspects of the tasks promote regulation (Hadwin et al., 2011; Järvenoja et al., 2015). We select project-based engineering as the context because it offers a multi-phased environment for self- and shared regulation to unfold (Galand et al., 2010; Järvelä, Kirschner, et al., 2016). Project-based experiences engage students in open-ended, learner-directed design challenges (Krajcik, McNeill, & Reiser, 2008). These tasks activate regulation to formulate understanding, strategies, coordination, and evaluation. Learners self-regulate by identifying the design goals and planning toward goals. Learners activate shared regulation to coordinate groups' emotion, strategies, and motivation, particularly when facing ill-structured design tasks (Järvenoja et al., 2018).

The phases of the design process in project-based engineering also overlap with the cyclical model of regulated learning. The design process may not always be linear, as engineer designers iteratively revisit design alternatives (Falk et al., 2014; Tonso, 2006). Evaluation and feedback occur cyclically to understand and develop design's function,

mechanism, and structure (Hatamura, 2006). To illustrate, observations of successful design practices reveal that experts (design practitioners) make preliminary evaluations of alternatives before execution and evaluation. These experts also regularly looped between building and monitoring, whereas novices tend to employ trial-and-error without much planning (Ahmed, Wallace, & Blessing, 2003; Atman, Cardella, Turns, & Adams, 2005). The focus on planning and monitoring resembles the distinction between highly regulated learners and novices: Learners who engage in effective task analyses and planning perform more efficiently than learners who spend little time on forethought before task execution (Zimmerman & Kitsantas, 2005).

In sum, strategic planning and evaluation resemble the reflective moves in regulated learning. Most research in engineering design processes, however, has been limited to examining self-regulation (Galand et al., 2010; Stefanou et al., 2013). This suggests a need to examine how groups jointly regulate strategies and exchange interactions in ill-structured design tasks.

2.4. Regulation as grounded in social exchange

Regulation processes in collaborative learning are grounded in social exchange among members (Järvenoja et al., 2015). We thus turn to social exchange theory to explore how differences in levels of general exchange with peers may explain the variation in learners' contributions to group-level regulation. Social exchange theory proposes that an individual exchanges resources with others, if the perceived usefulness of the exchange exceeds its costs and outweighs the benefits from alternative behaviors (Blau, 1964; Emerson, 1976).

Paradigms of costs and benefits from social exchange can be applied to regulatory behaviors in collaborative learning. Executing regulatory behaviors may incur costs, including cognitive costs for information retrieval, evaluation, and monitoring, and executional costs such as time and materials (Yan, Wang, Chen, & Zhang, 2016). At the same time, regulation can yield cognitive, metacognitive, and motivational benefits (Melzner, Greisel, Dresel, & Kollar, 2020; Zimmerman, 2000). Regulatory behaviors help learners create or enrich understanding, retrieve information, and systemize knowledge structures. Such behaviors can serve metacognitive purposes like fostering reflection and evaluation of learning processes to promote successful learning. Learners employ regulation as motivational strategies, such as when continuous regulatory exchange with peers helps to enhance individuals' contextual interest in learning (Melzner et al., 2020). How a learner evaluates the multi-faceted benefits and costs of regulation results in variation in their exchange of regulatory behaviors.

Learners who have more existing social ties (i.e., more social exchange) with peers in the course may perceive regulatory behaviors in collaborative settings as less costly or more beneficial than those with less peer exchange, and consequently, are more likely to engage in shared regulatory behaviors. From a cost perspective, when enacting regulatory behaviors, learners with existing social exchange ties may reach other peers more easily than those without such connections (Wasserman & Faust, 1994). Meanwhile, the benefits from regulatory behaviors may be higher for those with more general exchange, based on explanations of contact frequency and reciprocity, among others (Blau, 1964; Homans, 1961; Wellman & Wortley, 1990). Frequent, general contact facilitates support provision in times of needs (Homans, 1961). When encountering difficult learning problems, peers with general contact may be more likely to provide support to each other by initiating regulatory strategies, for example, to develop mutual understanding, shared evaluation, and group interest. In addition, learners may be more likely to engage in shared regulation, with the expectation of reciprocity in social exchange that peers are entitled to the same amount of giving and receiving (Blau, 1964). Learners with prevailing connections in the course (i.e., existing give-and-take relationships) may be more inclined to employ regulation strategies to help themselves and others achieve successful learning, with the expectation of future returns.

Individuals' different propositions to social exchange result in different group dynamics (Cropanzano & Mitchell, 2005). Groups whose members gravitate towards a high degree of social exchange may represent more interdependence (i.e., group outcomes are based on coordinated efforts). In contrast, a lack of social exchange may signify independence (i.e., outcomes are based on individuals' efforts). Furthermore, a large variance in general exchange from a student to others (i.e., "outdegree" exchange) may reflect varying levels of group's commitment to collaboration and shared regulatory behaviors, while little variance in social exchange may indicate more equal contributions (Sha & van Aalst, 2003). In short, group-level variation in social exchange can serve as an indicator for group engagement in regulatory processes. We build on this insight when selecting the participating teams for our study to represent high and low variances of exchange.

2.5. Regulation as key to successful learning

Regulation strategies that adapt to dynamic learning contexts help learners coordinate behaviors and goals in successful learning (Järvelä et al., 2015; Järvenoja et al., 2015; Zheng, Xing, & Zhu, 2019). Skilled self-regulated learners more frequently reflect on task requirements and devise alternative strategies to reach learning goals (Volet, Vauras, & Salonen, 2009). Meanwhile, shared regulation helps groups coordinate goal, emotion, and motivation, particularly in ill-defined tasks where simply relying on self-regulation is insufficient (Järvelä, Kirschner, et al., 2016). Facilitative co-regulation, where members support others' behaviors and goals may be associated with positive social interactions (Rogat & Linnenbrink-Garcia, 2011). To illustrate, Kwon, Liu, and Johnson (2014) classified "good collaborators" as those who formed early interactions in the course, demonstrated adaptive selections of group regulatory behaviors, and also showed continuous, positive socio-emotional interactions.

Regulation can also facilitate learning through efficacy beliefs (Zimmerman & Schunk, 2011). Skilled self-regulated learners may exhibit a high sense of efficacy in their abilities, which influences their commitment for knowledge and future goals they set for themselves (Zimmerman & Schunk, 2011). Emergent research has also found a positive link between group-level regulation and collective efficacy (Zheng, 2017). Collective efficacy encompasses perceptions of the group's ability to understand and execute tasks, generate ideas, and monitor progress. Students in groups with higher levels of shared regulation report higher efficacy of their group's ability (Zheng, 2017). Groups who report higher collective efficacy tend to show greater effectiveness in interdependent tasks, where the performance of one member depends on that of others (Alavi & McCormick, 2008; Gibson, 2001).

There is growing empirical support for the link between regulation and successful learning (e.g., Jermann & Dillenbourg, 2008; Kwon et al., 2014; Zheng et al., 2019). For example, Jermann and Dillenbourg (2008) conducted experiments on the effectiveness of providing student groups with graphical feedback about group dynamics and found that such feedback facilitated group-level planning and subsequent performance. Consistent with the theoretical grounding that self- and group-level regulations are complementary in learning, researchers have observed that successful problem-solving groups show more diverse and frequent activities in both self- and socially shared monitoring (Zheng et al., 2019).

3. Research questions and hypotheses

In sum, this study is situated in a project-based, collaborative undergraduate engineering course that provides opportunities to examine various processes of individual and shared regulation. Although prior work on regulation in project-based learning often relies on self-reported survey, the extant research on shared regulation illustrates the potential of using a more situated data source: student discourse (Malmberg et al.,

2017; Ucan & Webb, 2015). We thus use student discourse to explore the following questions:

RQ1. How do teams engage in project-based learning (PBL) in a collaborative engineering design course?

- How do regulation processes and types vary among teams that differ in members' frequencies of course-related social exchange?
- How does the sequence of regulation processes vary among student teams?

RQ2. How do team regulation patterns relate to individuals' learning outcomes, namely final course grade and perceived collective efficacy?

We develop the following hypotheses:

H1. a. Teams whose members report more frequent social exchange may demonstrate more frequent socially shared regulation, compared to teams with less frequent social exchange.

b. The sequence of regulation also depends on individuals' exchange: Teams with higher levels of social exchange engage in more shared planning and monitoring (Molenaar & Chiu, 2014; Zimmerman & Kitsantas, 2005).

H2. Teams whose members demonstrate higher levels of shared regulation report higher collective efficacy and better learning performance (Zheng, 2017).

4. Method

In this study, we used sequential mixed method approaches (Creswell & Clark, 2017), combining qualitative discourse analysis to code the regulation types and phases with quantitative approaches to examine the differences among teams. We then applied correlational study design to explore the relations between regulation and learning outcomes.

4.1. Study setting

The study took place in a two-term, first-year project-based introductory engineering course in a large, selective U.S. public research university in the 2018–2019 academic year. The goal of this elective course is to introduce students to fundamental engineering design principles (e.g., design process), specific engineering concepts (e.g., fluid mechanics, circuitry), and software and technical skills (e.g., computer-aided design, electrical fabrication). Students self-selected into the course. The course consisted of weekly 2-h lectures and 2-h laboratory sessions in the first term, and 1-h lectures and 2-h labs in the second term.

PBL was integrated in both terms of the course (Nguyen, Wu, Fischer, Washington, & Warschauer, 2020; Wu, Fischer, Rodriguez, & Washington, 2018). Students participated in the full cycle of project development. The first term introduced students to practical engineering design skills and concepts, so that they could continue the second term with an autonomous project that involved programming, using sensors and microcontroller, and advanced manufacturing. The course required students to develop business plans based on their projects to mirror real-world engineering practices. Students created project milestones in teams and verbally presented their weekly progress during labs. Student teams delivered two design presentations at mid-term and the end of the term to peers and the lab instructors.

Collaborative learning is a central aspect of this PBL course. The course encouraged students to form their own teams of four to six in the second term and meet at least once a week outside of class to work on their projects. Students met during the weekly laboratory sessions to ideate, design, build, and evaluate their autonomous projects.

4.2. Social exchange ties

Prior to students' selecting their own teams in the second term, all students in the course ($n = 211$) were surveyed about their course-related social exchange. Students were asked to identify up to eight peers they would turn to for knowledge exchange (e.g., working in teams, seeking help for engineering-related tasks, discussion of engineering-related topics) in the class, and the weekly frequency that they leveraged those resources. Self-reporting interactions with others is a commonly employed methodology in network analysis (Wasserman & Faust, 1994). We selected individual-level outdegree exchange ties (student to others) instead of other measures such as indegree (others to students) or network-level centrality, to capture individuals' explicit exchange efforts as a proxy for their commitment to shared regulation. Social exchange ties were calculated as $(\text{number of peers}) \times (\text{interaction frequency})$. Most students reported interacting with 4–5 peers once a week.

4.3. Participants

Four teams were purposefully sampled to represent a range of mean and deviation in social exchange among team members (i.e., high versus low mean across team; high versus low variation within each team). The sample represents the overall course demographics (22.7% women, 72.7% Latinx or Asian students). Compared to the national sample of college students intending to pursue engineering majors in the United States (20.6% women, 28.8% underrepresented minority; Eagan, Hurtado, Figueroa, & Hughes, 2014), our sample was similar in terms of gender, but was more ethnically diverse. ANOVA of participants' grade in the first term of the course suggested no significant difference among teams, $F = 2.68$, $p = .08$. Because the study happened midway through the course, we were not able to collect other indicators of learner characteristics, such as baseline motivation. The details about each team are as follows.

Team HighHigh (high mean, high variation) showed a high variation in social exchange, but its members reported high course-related knowledge exchange with peers on average ($M = 6.60$; $SD = 1.52$; first term grade $M = 99.39$, $SD = 1.81$). The team included two females (one White and one Latinx) and three male students (one Latinx and two White).

Team HighLow (high mean, low variation) included one female (Latinx) and five male students (two Latinx, one Asian, and two White). The team reported overall high levels of social exchange ($M = 5.20$; $SD = 0.44$; first term grade $M = 97.39$, $SD = 2.50$).

Team LowHigh (low mean, high variation in social exchange) included two female (both Latinx) and four male students (one Latinx, two Asian, and one White). The team reported low level of social exchange, with variation ($M = 4.00$; $SD = 1.22$; first term grade $M = 98.47$, $SD = 2.55$).

Finally, team LowLow (low mean, low variation) consisted of one female student and four male students. All members are Latinx. Overall, team LowLow's students reported slightly below average frequencies of social exchange, with little variation, prior to team formation ($M = 4.50$; $SD = 0.58$). The team's average first term grade was 94.82, $SD = 3.75$.

The four teams worked on two autonomous projects. Teams HighHigh and LowLow were in the same lab session to design an autonomous quadcopter, whereas teams HighLow and LowHigh worked in another lab session on a fitness tracker. Similar technical topics in both projects were programming, circuitry, sensors, and advanced manufacturing (3D printing and laser cutting).

Each project involved similar phases of collaborative design. Student teams had to plan and evaluate their designs against requirements for size, structure, accuracy, safety, and budget. Iterative planning and evaluation necessitated self- and group-level regulation, as students had to collaborate to create and test prototypes, produce design reports, and present on the prototypes.

4.4. Data collection and instruments

Analyses drew from the audio transcripts of the teams' discussion (three sessions per team; 24 h of audio data; $n = 7514$ conversational turns). Teams carried out discussion in lab. A recorder was placed on each team's table for each session, after obtaining student consent through the Institutional Review Board. The discussion was audio recorded and subsequently transcribed. Data collection was conducted from the mid-point to the end of the second term, when students were already familiar with fundamental engineering principles and focused on programming and manufacturing their group products. At the end of the term, we collected the course grade and surveyed participants for collective efficacy. We developed deductive codes for regulation processes and types and applied epistemic network analysis (ENA) and process mining on the coded datasets. The analytic procedure is outlined below.

4.4.1. RQ1. Regulation models and processes

Deductive codes for regulation models and processes were developed based on prior literature (Hadwin et al., 2011; Järvelä et al., 2015; Malmberg et al., 2017). The unit of analysis was each turn of talk by a student during group discussion, but the analytical decision of which code the unit received was placed in the larger context of team discussion, to determine whether students were working towards self or shared regulatory goals in the broader discourse. The context window spanned up to 10 talk turns; 5 prior to and 5 following the unit of talk. We created binary codes (1: present; 0: absent) for regulation type (i.e., self; shared regulation) and process (i.e., task understanding, strategic planning, motivation beliefs, collaboration, progress monitoring, reflection, or off-task). A talk unit always received a code for process (e.g., shorter utterances such as "Thanks" could fall under a Collaboration episode), whereas we only coded for regulation type if the talk unit specifically indicated an intent to regulate students' own ("I" perspective) or team's efforts ("we" perspective; Malmberg et al., 2017). The coding scheme was refined during four iterative coding and negotiation cycles between the first and second authors, using 15% of the dataset. The initial coding scheme included codes for self, co, and socially shared regulation. However, due to the low occurrence of co-regulation in our sample of 15% of the data (2/1127 occurrences; 0.2%), the final codebook excluded co-regulation. The focus on self- and shared regulation reflects our initial hypothesis that project-based tasks likely activate these two processes (Järvelä, Kirschner, et al., 2016). However, we note that because the code for each talk turn was determined by the larger context and explicit talk intent, the prevalence of regulation type (i.e., self, co, and shared) might be an artefact of the coding scheme.

To establish reliability, the first author and a research assistant recoded the 15% of the codebook dataset and an additional 10%. Acceptable inter-rater agreement was established for the second round of coding, Cohen's $\kappa = .75$ for regulation types and $.87$ for processes. The first author then used the codebook to code the remainder of the dataset. The appendix outlines the codebook with exemplary discourse.

4.4.2. RQ2. Course grade and perceived collective efficacy

The grade data included the final and component grades (e.g., attendance, assignment, final project). At the end of the second term, all participants were also surveyed for their perceived collective efficacy. The survey was adapted from Alavi and McCormick (2008) and included statements about individuals' perceptions of their group's ability to identify key issues, complete tasks in available time, systematically present results, put theory into practice, achieve consensus in a reasonable time, and generate ideas as a group. The items were 5-point Likert-type scale (least to strongly confident). Prior work had found these items to show acceptable internal reliability and fit statistics (Alavi & McCormick, 2008). The adapted survey showed acceptable internal consistency with our study sample (Cronbach's $\alpha = 0.79$).

4.5. Analytical approaches

4.5.1. Overview of methods to analyze regulation temporality

Researchers have employed frequency analyses such as activity counts to analyze regulation in collaborative discourse (e.g., Malmberg et al., 2017). A limitation to frequency analyses is that they may not account for the temporal aspects of the dialogues (Stribos, Martens, Prins, & Jochems, 2006). To address this limitation, a recent review indicates the potential of network and process analyses to capture the occurrences and sequence of regulatory processes (Järvelä et al., 2019). These advancements in the field inspire the analytical approaches in our study: Epistemic network analysis (ENA; Shaffer, 2017) and process mining (Romero, Ventura, Pechenizkiy, & Baker, 2010). ENA allows for the examination of activities as a coherent network, while process mining accounts for sequential relations.

Epistemic Network Analysis. ENA is a network analysis technique to investigate associations between a set of highly dynamic elements (Shaffer, 2017). The methodology was developed based on the assumption that the structure of connections among cognitive elements plays a more crucial role in understanding learning progress than the presence or lack of separate components (Shaffer et al., 2016). Two elements are considered connected if they appear in the same text window, such as in the same selection of student's messages. The contrast between networks can be examined through comparing their nodes and connections.

ENA has shown promise in visualizing co-occurrence of cognitive skills and social exchange (Gašević, Joksimović, Eagan, & Shaffer, 2019; Shaffer et al., 2016). Gašević et al. (2019), for example, illustrated the added values of linking students' epistemic network to their social exchange. Students who succeeded in the class produce more process-related topics and higher responsiveness to peers (Gašević et al., 2019). In this study, we applied ENA to examine the co-occurrence of regulation processes and types.

Process mining. Process mining identifies process models from data, such as log files or verbal transcripts, under the assumption that sequential events are governed by one or more processes (Bannert et al., 2014). This view emphasizes that the whole process reflects the underlying construct of learning. It is particularly relevant in the context of regulated learning on the basis that a mental structure or learning strategy guides the regulatory process (Bannert et al., 2014). Process models are presented as Petri Nets, which are directed graphs with a finite set of nodes for places (e.g., start and end points) and transitions (e.g., activities), with specifications for the directions from places to transitions and vice versa. Researchers have applied process mining to identifying different event sequences in self-regulation for higher performing learners (Engelmann & Bannert, 2019).

4.5.2. RQ1.a. Regulation co-occurrences

Epistemic network analysis (ENA; Shaffer, 2017) was used to analyze the structures of regulation networks of the four teams, using data from all three weeks. Co-occurrences of regulation mode and process were inputted as a binary matrix within 4-talk-unit windows (1: co-occurred; 0: did not co-occur). Each adjacency matrix was normalized (i.e., converted into vectors, then divided by its length). Normalization helps to present the relative frequencies of code co-occurrences independent of the variation in total conversational turns across teams (Shaffer et al., 2016).

Next, ENA performed singular value decomposition to visualize the high-dimensional vectors along x and y axes. Node positions were calculated using summed adjacency matrices.

The differences between regulation networks were examined with subtraction networks. This method subtracts the connection weight of each node in the respective networks for visualizing the difference. The line color indicates which of the two networks contains the larger connection. Darker and thicker lines indicate greater differences in connection strength (Shaffer et al., 2016). Last, nonparametric

Mann-Whitney tests were conducted to compare the network means between student teams at the $p = .05$ significance level.

4.5.3. RQ1.b. Regulation processes

The temporal sequence of team’s regulation processes was examined through process mining (Janssenswillen et al., 2019). The data were transformed into event log format to represent the code at a specific point in time (i.e., Team, Code). The algorithm created one precedence matrix per group per week by using the absolute frequencies of preceding and subsequent codes. The reason for conducting the analysis at the week level was to account for the timestamps in weekly interactions. The darker box colors in the model suggest higher code frequencies, indicating that several group members have moved from the first to the second state/activity or performed the same code several times (i.e., self-loops). Following the results from process mining, we presented excerpts of team discourse to illustrate variation in collaboration patterns and sequence. All names are pseudonyms.

4.5.4. RQ2. Course grade and perceived collective efficacy

The second research question explored the association between team’s regulation patterns and learning outcomes. Towards this goal, we conducted the nonparametric Mann-Whitney tests to examine whether there was any significant difference in the final grades and collective efficacy for students in teams that employed a range of regulation activities (i.e., complex epistemic network) and teams that did not.

All students from each team appeared in the discussion transcripts and submitted the collective efficacy surveys. One student did not fill in the initial social exchange survey and was excluded from the calculations of the team’s average and standard deviation of exchange. Analyses were conducted in R 3.6.1 (R Core Team, 2019). ENA was conducted using the ENA web tool (Marquart, Hinojosa, Swiecki, Egan, & Shaffer, 2018).

Table 1
Proportion of individual and Team’s regulation type and processes per sessions.

	Regulation Type						Process											
	Total talk/n		Self		Shared		Understand		Plan		Collaborate		Motivation		Monitor		Reflect	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
HighHigh	154.25	104.74	.13	.06	.57	.16	.08	.06	.17	.08	.60	.14	.03	.02	.09	.05	.02	.03
Cam	127.67	86.52	.12	.06	.63	.02	.13	.10	.24	.03	.45	.06	.01	.01	.12	.06	.03	.03
Charlie	260.67	55.30	.16	.01	.49	.16	.05	.06	.17	.08	.68	.12	.04	.01	.06	.04	.01	.01
Chris	168.00	32.53	.11	.05	.45	.19	.03	.02	.08	.06	.75	.20	.05	.04	.08	.07	.00	.00
Annie	141.00	181.02	.20	.04	.69	.22	.09	.02	.16	.12	.55	.09	.02	.03	.10	.08	.05	.04
Valerie	34.00	4.24	.06	.05	.60	.20	.08	.03	.15	.02	.63	.02	.02	.02	.08	.03	.00	.00
HighLow	129.81	103.69	.08	.04	.44	.22	.07	.06	.13	.10	.62	.22	.02	.03	.08	.06	.01	.01
Ben	157.00	185.26	.10	.04	.34	.21	.05	.04	.13	.03	.72	.02	.04	.05	.06	.02	.01	.01
Daniel	.50	.71	.00	.00	.00	.00	.00	.00	.00	.00	.50	.71	.00	.00	.00	.00	.00	.00
Anthony	136.00	55.65	.09	.06	.46	.17	.05	.05	.14	.07	.71	.10	.01	.01	.07	.04	.01	.01
Timmy	80.00	68.51	.07	.04	.69	.05	.09	.01	.18	.13	.47	.11	.06	.04	.17	.03	.00	.01
Mitchel	186.67	152.40	.09	.04	.56	.04	.14	.11	.14	.14	.61	.08	.02	.02	.10	.06	.01	.01
Pat	184.67	43.09	.09	.01	.42	.07	.06	.04	.14	.11	.69	.12	.02	.02	.06	.03	.01	.02
LowHigh	96.17	54.74	.10	.07	.30	.10	.02	.03	.09	.05	.74	.12	.02	.02	.06	.03	.00	.00
Bella	98.00	66.19	.08	.01	.35	.09	.02	.03	.12	.01	.71	.08	.02	.00	.07	.05	.00	.00
Chris	155.00	2.34	.17	.12	.35	.21	.05	.02	.12	.12	.69	.12	.01	.02	.06	.03	.01	.01
Elizabeth	81.33	76.14	.05	.07	.22	.11	.01	.01	.09	.03	.73	.20	.01	.01	.06	.06	.00	.00
Jeon	50.00	22.65	.10	.07	.24	.12	.01	.01	.12	.02	.72	.10	.05	.05	.05	.03	.00	.00
Leon	93.00	19.97	.07	.06	.31	.04	.02	.03	.07	.04	.81	.06	.01	.00	.06	.03	.00	.01
Omar	98.00	72.96	.13	.10	.30	.10	.04	.04	.05	.01	.73	.17	.02	.02	.04	.02	.00	.00
LowLow	122.40	67.63	.02	.02	.24	.11	.08	.03	.07	.05	.68	.13	.00	.00	.30	.11	.00	.00
Andy	119.67	47.82	.03	.01	.27	.15	.07	.03	.08	.05	.70	.12	.08	.02	.26	.03	.00	.00
Emanuel	155.00	57.00	.02	.01	.24	.10	.09	.01	.09	.02	.68	.05	.07	.03	.37	.02	.00	.00
Jake	152.00	93.34	.04	.01	.29	.18	.10	.04	.06	.03	.62	.03	.11	.00	.32	.08	.00	.00
Jose	29.33	28.01	.00	.00	.14	.07	.05	.05	.02	.03	.69	.30	.02	.04	.14	.12	.00	.00
Pam	137.33	43.25	.03	.04	.25	.13	.08	.01	.10	.05	.73	.04	.04	.01	.37	.06	.00	.00

Notes. HighHigh = High Mean, High Variance; HighLow = High Mean, Low Variance; LowHigh = Low Mean, High Variance in perceived social exchange; LowLow = Low Mean, Low Variance. All student names are pseudonyms. Off-task proportions are not reported in the Process columns; M of processes may not add up to 1.

5. Findings

5.1. RQ1. Teams with more frequent social exchange had more frequent regulation patterns

Overall, all teams engaged most frequently in collaboration ($M = 0.60-0.74$, $SD = 0.12-0.22$) and least in reflection ($M = 0.00-0.02$, $SD = 0.00-0.03$). The descriptive statistics in Table 1 can be interpreted as follows: generally, 60%–74% of observed interactions in the teams were coded as collaboration, and only 0%–2% for reflection. There was a wide range of frequency of shared regulation across teams ($M = 0.24-0.57$, $SD = 0.10-0.22$). Teams HighHigh and HighLow, the two teams with more frequent social exchange, showed higher engagement in shared regulation ($M = 0.57$, $SD = 0.16$, and $M = 0.44$, $SD = 0.22$, respectively). Although we noticed that the two teams with more shared regulatory patterns had a lower percentage of underrepresented minority students, the Mann-Whitney test did not indicate a significant difference in the average number of conversational turns between underrepresented and other students in those teams ($W = 71$, $p = .24$).

5.2. RQ1a. Differences in co-occurrences of regulation processes and types

ENA revealed that the most frequent co-occurrence across the four teams is Shared Regulation and Collaboration. Notably, the two teams that reported more frequent social exchange overall (HighHigh, HighLow) appeared to engage in more dynamic collaboration patterns. In these teams, there was more shared regulation of planning, progress monitoring, and task understanding, instead of just regulation and collaboration.

Fig. 1 shows the subtraction networks among the teams (represented by different colors). The squares represent the centroid (i.e., mean) for

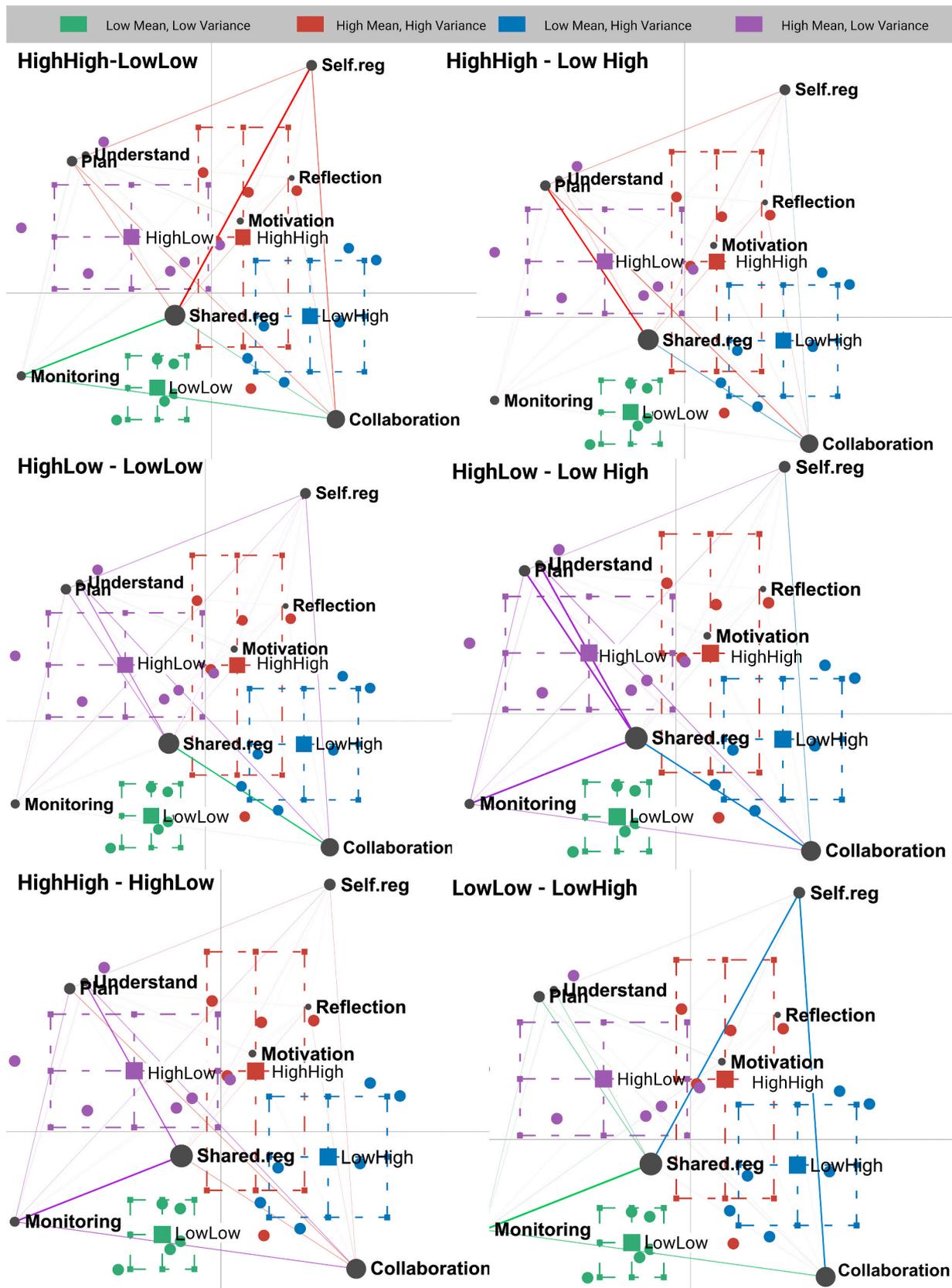


Fig. 1. Comparison among groups in epistemic network
Notes. The squares represent the mean (centroid) for each team, the colored dots represent the students, and the black dots represent codes (regulation types and processes). Darker lines suggest more frequent co-occurrences of regulation types and processes within a 4-turn talk window. For example, when comparing team HighHigh and LowHigh, we observed more shared regulation of planning in team HighHigh, as indicated by the red line between “Shared.reg” and “Plan”. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

each team, the colored dots represent the students, and the black dots represent the regulation types and processes. Larger black dots indicate higher frequency of occurrence, for example, shared regulation and collaboration were represented by the biggest dots. The network structures can be characterized as follows: along the y axis, towards the top is self-regulation; towards the bottom is shared regulation; along the x axis, towards the left are task understanding, strategic planning, and monitoring; and towards the right are reflection, motivation, and collaboration. The highlighted lines in the subtraction networks demonstrate the differences between the two team's epistemic networks. Take the subtraction network of team HighHigh (red lines) and team LowLow (green) from the top left corner of Fig. 1 as an example. The red lines indicate that HighHigh had more links between shared regulation and all regulation processes, particularly planning, compared to LowLow.

Next, we performed Mann-Whitney tests to examine differences in team regulation structures. The regulation patterns of HighHigh were significantly different from those of team LowLow along both the x and y

axes (x: $Mdn\ HighHigh = 0.37, Mdn\ LowLow = -0.46, U = 25, r = -0.83, p = .01$; y: $Mdn\ HighHigh = 1.00, Mdn\ LowLow = -1.00, U = 23, r = -0.84, p = .03$). The regulation patterns of team HighLow were significantly different from those of team LowLow along the y axis (y: $Mdn\ HighLow = 0.39, Mdn\ LowLow = -1.00, U = 30, r = -0.86, p < .001$) but not the x axis (x: $Mdn\ HighLow = -0.74, Mdn\ LowLow = -0.46, U = 13, r = 0.13, p = .79$). Patterns of team HighLow were also different from those of team LowHigh along the x axis (x: $Mdn\ LowHigh = 1.00, Mdn\ HighLow = -0.74, U = 36, r = -0.80, p < .001$) and y axis (y: $Mdn\ LowHigh = -0.31, Mdn\ HighLow = 0.39, U = 6, r = -0.67, p = .05$).

These results suggest that HighLow and HighHigh generally demonstrated different patterns of self and shared regulation (along the y-axis), compared to the other two teams. Comparisons along the x axis suggested a difference in focus on planning (e.g., HighLow) and just collaboration (e.g., LowHigh). There was no significant difference between groups with low social exchange or between groups with high exchange (i.e., HighHigh-HighLow; LowHigh-LowLow).

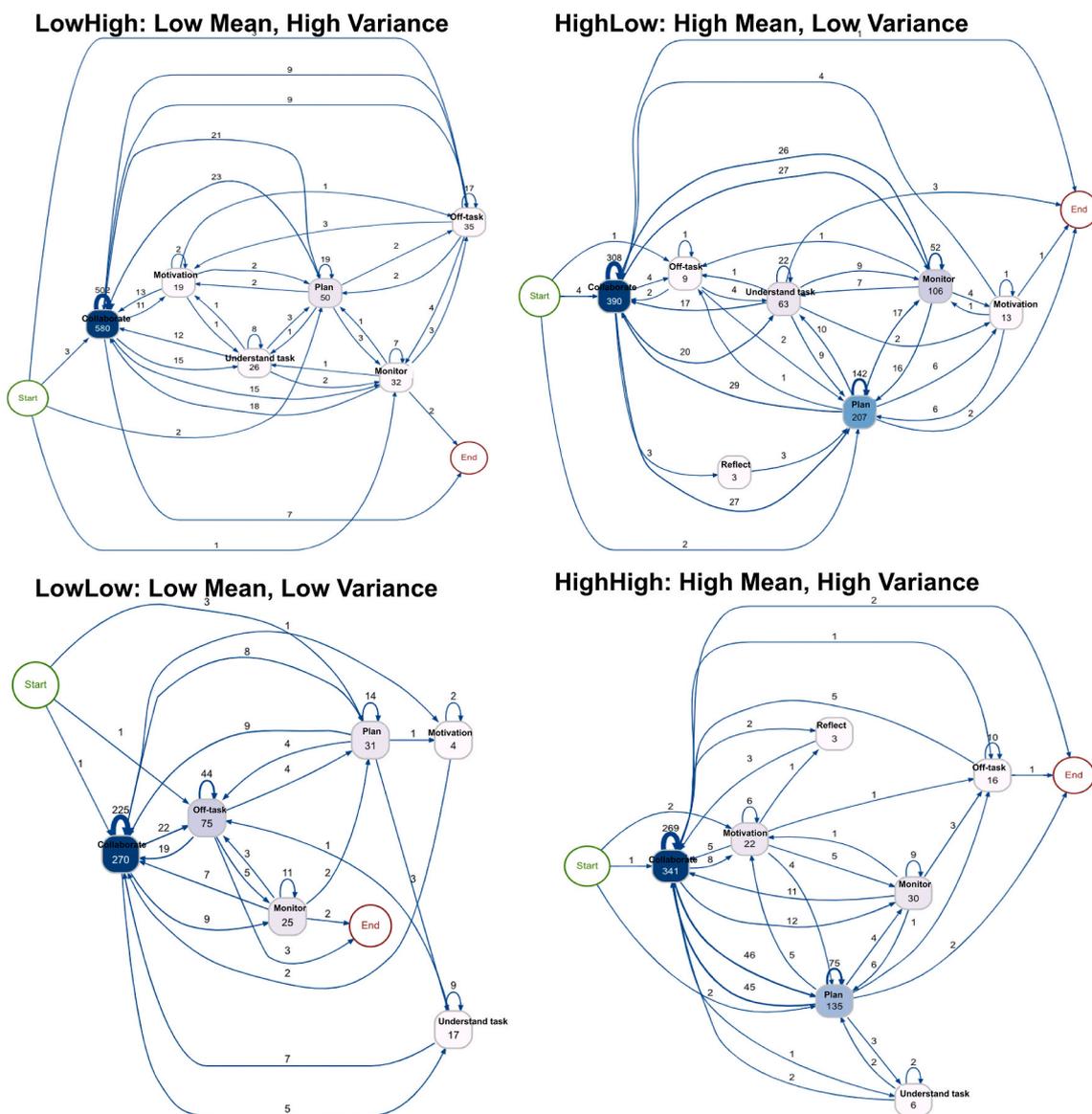


Fig. 2. Comparison among groups in process maps from the mid-term week **Notes.** The number indicates occurrences of each process (e.g., plan, monitor, motivation, etc.) and transitions between processes. Arrows indicate directions, where students moved from one process to the other. Bigger and darker colors indicate higher frequency. For example, the figure suggests that self-loops for collaboration is the most prevalent in each group, as indicated by the darkest blue color. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

5.3. RQ1b. Differences in regulation processes

The process maps suggested the same patterns as the ENA: Groups whose members reported more frequent social exchange overall had more complex process models. Whereas teams LowLow and LowHigh were mostly engaged in Collaboration – Collaboration (high frequency codes, high frequency self-loops), the teams with larger social exchange engaged for longer in other collaboration phases, such as Collaboration – Planning – Planning. Because these patterns were largely consistent across teams across weeks, we chose one week (the term’s midpoint) to illustrate the regulation processes in each team (Fig. 2).

The figure indicates more connections among the regulation phases in HighHigh and HighLow, suggesting that these teams engaged in more fluid transitioning, as opposed to jumping back and forth between collaboration tasks. Both teams had a high frequency of strategic planning and self-loops for planning (Team HighHigh: $n = 135$, self-loops = 75; Team HighLow: $n = 207$, self-loops = 142), and team HighLow also frequently engaged in progress monitoring ($n = 106$, self-loops = 52).

Meanwhile, in teams LowHigh and LowLow, there was less engagement in other regulation processes, such as planning. The frequencies and self-loops for off-task talks in teams LowHigh and LowLow appeared to be higher than teams with high overall social exchange (frequencies: HighHigh: 16; HighLow: 9; LowHigh: 35; LowLow: 75). Moreover, even when teams LowLow and LowHigh started planning or monitoring, the self-loops for these processes had a low range (2-19). This suggests that these teams did not appear to have stayed in those processes for long before transitioning back to collaboration.

5.4. RQ1b. Illustrative examples

Excerpts of the discourse from the same lab session of teams HighLow and LowHigh provide insights into nuances in teams’ regulation. Team HighLow first divided the tasks, then worked alongside each other. Consider an excerpt from Pat, Timmy, and Anthony (pseudonyms), who were working together on a temporary breadboard (Table 2). The three first checked in on their understanding of the wiring diagram, then worked on the breadboard and checked in again for a new task.

Within this excerpt, the students contributed quite evenly and transitioned among the regulation phases. Team members expressed their motivation beliefs about the task during collaboration. Pat, Timmy, and Anthony all engaged in shared regulation to check whether they agreed on tasks (e.g., “we used”, “we were going to”, “we will”). The longer duration of joint engagement in planning and monitoring marked the rest of the team’s lab session.

In contrast, team LowHigh immediately started building their design at the start of the session (Table 3). The conversations were primarily between Chris and Leon, who went back and forth between writing the codes and stepping outside of the lab to test. Chris and Leon were focused on testing their codes, debugging (fixing the errors), and testing the codes again. The conversation was thus mostly centered around execution, with one-off planning before turning back to collaboration. Contrary to HighLow’s fairly even distribution of talk turns, the conversation was primarily led by Chris. There was no explicit discussion of shared goals or task execution, but instances of self-regulation (e.g., “Let me figure out which statements I need”). Although the other team members appeared in the group dialogue later in the recorded lab session, the conversation pattern was largely unchanged—long duration of collaboration followed by short turns of monitoring and planning.

5.5. RQ2. Team’s regulation patterns were related to collective efficacy

RQ2 examined the association between team’s regulation patterns and learning outcomes. We performed the Mann-Whitney test to examine whether individuals in HighHigh and HighLow had significantly different learning outcomes from those in LowHigh and LowLow.

Table 2
Excerpts from team HighLow.

Speaker	Talk	Code
Timmy	Did you understand this?	Task Understanding
Pat	Yeah	Task Understanding
Timmy	Cool, because I want to learn more.	Motivation; Self-Regulate
Timmy	I feel like I su** at the breadboard.	Motivation; Self-Regulate
Anthony	Where do they have the diagram?	Task Understanding
Timmy	It should be on the drive?	Task Understanding
Anthony	The wiring diagram, yeah, but that’s for the beetle.	Task Understanding
Anthony	I don’t know for the Arduino.	Task Understanding
Timmy	It’s pretty similar.	Task Understanding
Anthony	I just know that there should be one digital and two analogs.	Task Understanding; Shared Regulate
Timmy	Ya, no, we can do that on the Arduino.	Task Understanding; Shared Regulate
Anthony	Uh do you have the LED?	Collaboration; Shared Regulate
Anthony	Do you know which register is which?	Collaboration; Shared Regulate
Pat	Are we using registers?	Collaboration; Shared Regulate
Anthony	Yeah, for the LED.	Collaboration; Shared Regulate
Pat	We used the brown one last time.	Collaboration; Shared Regulate
[The three worked on the analogs for about 20 talk turns]		
Pat	Let’s make a bus line!	Strategic Planning; Shared Regulate
Timmy	I think we were always going to do a bus line right?	Strategic Planning; Shared Regulate
Anthony	Yeah, because we were going to connect the accelerometer and the barometer.	Strategic Planning; Shared Regulate
Timmy	That’s what I’m saying. Let’s get some soldering going.	Strategic Planning; Shared Regulate
Anthony	No, we can use this as a bus line.	Strategic Planning; Shared Regulate
Timmy	Yeah, but I’m saying in the future we’ll solder it.	Strategic Planning; Shared Regulate
Anthony	Oh yeah we will definitely.	Strategic Planning; Shared Regulate
Timmy	But for now we’ll do this.	Strategic Planning; Shared Regulate
Timmy	But all of these are so confusing.	Motivation; Self-Regulate

Teams HighHigh and HighLow were selected as the comparison because they showed more regulation patterns in the ENA and process mining. Results suggest a statistically significant difference in collective efficacy for students in the teams with more dynamic patterns, compared to the other two teams ($W = 25.5, p = .04$).

There was no significant association between regulation patterns and students’ final course grades ($W = 34.5, p = .09$). There are two potential explanations for this result. First, there was little variation in the final grades in this first-year elective class (Fitness Tracker: $M = 95.85, SD = 4.94$; Quadcopter: $M = 92.94, SD = 4.57$; our sample’s grade $M = 95.38/100, SD = 3.25$). Second, the small sample size limited our analysis’s power to detect small or medium effects. However, we observed that the two teams who demonstrated more regulation patterns scored higher on the final project, which reflected their collaborative work in creating group presentation and design report (HighHigh = 93%; HighLow = 93%; LowLow = 91.5%; LowHigh = 83%).

6. Discussion

This study examined the co-occurrences and sequence of regulated learning in collaborative engineering design. Results illustrate the promising use of temporal analyses to uncover nuances in regulation processes. Findings have implications for group work arrangements to promote discourse that is conducive to the design process and highlight a future direction to explore the scaffolding of regulation strategies in collaboration.

Table 3
Excerpt from team LowHigh.

Speaker	Talk	Code
Chris	Okay, back to hardcoding.	Collaboration
Chris	We are still going back to the statement.	Collaboration; Shared Regulate
Chris	Okay, that should work. I hope it works.	Motivation; Self-Regulate
Leon	Are you going to repair them?	Collaboration; Shared Regulate
Chris	If this is turning up, thank you.	Collaboration; Shared Regulate
Chris	Let me figure out which statements I need.	Collaboration; Self-Regulate
Chris	Going to check step 1.	Collaboration; Self-Regulate
Chris	Okay let's go test.	Collaboration; Shared Regulate
	[Upon returning from testing, the two students immediately delved into further building]	
Chris	Is this the one that had the calibration or not?	Strategic Planning; Shared Regulate
Chris	Okay, no, we don't need the calibration yet.	Strategic Planning; Shared Regulate
Leon	You do have a calibration. Yeah.	Strategic Planning; Shared Regulate
Chris	I thought I took that out.	Collaboration
Chris	It shouldn't be moving.	Collaboration
Leon	Is it this?	Collaboration
Chris	I forgot to change this	Collaboration; Self-Regulate
Chris	Okay, I just need to get this one to work.	Collaboration; Self-Regulate
Leon	Okay.	Collaboration
Chris	Okay, good. Let's go back outside.	Collaboration; Shared Regulate

6.1. Social exchange reflects different regulation patterns

The ENA results suggest that teams who reported more frequent social exchange prior to team appointment more often focused on iterative planning and evaluation, as opposed to just execution. In particular, these teams tended to demonstrate more shared regulation of planning, task understanding, and reflection, compared to teams with low frequencies of social exchange. We did not find a significant difference in the regulation networks between teams with high versus low variation in team members' overall social exchange. This result aligns with research on diverse group cognitive complexity, which suggests that motivated members initiate cognitive activities such as coordination and planning in ways that increase the group's overall cognitive complexity and task performance (Curşeu & Pluut, 2013).

These findings should be interpreted in light of the research on project-based engineering and regulation in collaborative learning. More deliberate planning and evaluation in design have been associated with higher quality products (Ahmed et al., 2003; Hatamura, 2006). For example, researchers have found that first-year students who spent more time evaluating and choosing among design alternatives produced solutions of higher quality than those who went straight to building (Atman et al., 2005). The findings echo prior work that differentiates regulatory processes in expert versus novice regulators: Experts tend to engage in more effective task analyses and planning (Zimmerman & Kitsantas, 2005).

Why did student teams in their first engineering elective demonstrate different levels of engagement in shared regulation of planning, collaboration, and monitoring, even though their baseline academic performance (i.e., first term grade) did not significantly differ? Our findings suggest that beyond prior knowledge, students may have different preparedness for applying regulatory strategies and contributing to knowledge building efforts (Pintrich, 2000). Students who are more involved in collaborative exchange may be more likely to facilitate group-level task analyses and planning in early regulation phases. In turn, socially shared regulation helps the group to establish mutual understanding and aid task execution in later regulation phases (Kapur, Voiklis, & Kinzer, 2008). Thus, attending to different regulation patterns may surface potential variation in learners' experiences and highlight

how learners may contribute to and potentially gain from collaborative discourse.

6.2. Regulation as a process model

Findings from process mining illuminate how regulation phases can facilitate subsequent regulation. We found that when students were engaged in building, they tended to persist in their current activities, resulting in multiple self-loops in all teams. Meanwhile, socially shared tasks such as planning or monitoring may follow discussion of task understanding and precede either more collaboration, or more planning and monitoring followed by collaboration. These patterns are consistent with feedback loops in regulated learning, such that monitoring activities drive subsequent execution activities (Molenaar & Chiu, 2014). Notably, the long durations of planning and monitoring that we found in teams HighHigh and HighLow align with the patterns observed in socially engaged groups (Zheng et al., 2019). Whereas groups who performed more successfully often employed regulatory activities that began with execution and ended with monitoring, less successful groups solely relied on execution (Zheng et al., 2019).

Findings about how learners move through regulation phases contribute to our understanding of shared regulation as a process model (Järvelä et al., 2019). Researchers have emphasized the need to examine not only how individuals initiate regulated learning, but also how they maintain cognitive, affective, and behavioral engagement in forethought, performance, and evaluation, and initiate subsequent cycles of regulation (Järvelä et al., 2015; Zimmerman, 2000). Our findings suggest that groups who are more engaged in social exchange may transition more fluidly through task analyses, execution, and evaluation, and consequently engage in more regulation cycles to track their performance over time.

6.3. Regulation patterns are correlated with collective efficacy

We found a significant difference in collective efficacy between students in teams that displayed more complex regulation interactions and teams that did not. Collective efficacy can predict group performance in interdependent tasks (Gibson, 2001). The focus of collaborative design is to prepare students for collaboration in real-world practices (Mills & Treagust, 2003). Thus, fostering students' group efficacy is an important learning outcome (Krajcik et al., 2008). Additionally, efficacy has been found to be associated with attitudes towards the discipline and intention to pursue science and engineering careers, particularly among female and underrepresented minority students (Jones, Paretti, Hein, & Knott, 2010). Our results suggest that dynamic regulation patterns in groups, as opposed to mere execution, may be related to how students perceive their group effectiveness. Perceived efficacy beliefs may in turn influence the future goals and commitment to regulation that learners set for themselves and their groups (Zimmerman & Schunk, 2011).

6.4. Practical and methodological contributions

This study has three main contributions. First, findings have practical implications for how instructors can arrange student groups to promote discourse that is conducive to the design process. Teams who generally reported frequent social exchange demonstrated more shared regulation of planning, monitoring, and evaluation. Social exchange may facilitate commitment to knowledge building efforts in general and motivate students to employ a wider range of regulation strategies. Additionally, it is possible that social exchange may be a proxy for other student characteristics, such as baseline knowledge or more in-depth measures of self-efficacy that instructors may not have time to collect and analyze at the beginning of the course. Thus, instructors can consider briefly surveying students' social exchange frequency as one of the learner characteristics prior to assigning groups, to gain insights that better

facilitate group-level regulation.

Second, findings highlight a future direction to explore how regulation strategies can be scaffolded in collaborative learning. Regarding the relatively few instances of reflection and planning in some team discourse that we observed in this study, reflection prompts can be embedded into the team design processes (Engelmann & Bannert, 2019). Research on shared regulation in collaborative learning has underscored the effectiveness of explicit scaffolds for students to externalize their own and others' learning process (Gašević, Adesope, Joksimović, & Kovanović, 2015; Järvelä, Malmberg, & Koivuniemi, 2016). These techniques particularly pertain to groups with fewer regulatory activities that often fall back on trial-and-error.

Third, from a methodological standpoint, we demonstrate the use of statistical methods to visualize discourse data in ways that traditional discourse analyses may not afford. Researchers have pointed out two main limitations to employing process mining. First, process mining incorporates the activities of all subjects in the model with equal weighting, and thus fails to differentiate whether one or many individuals contribute to sequences in cognitive behaviors (Melzner, Greisel, Dresel, & Kollar, 2019). Second, examining differences in the process models of different groups on a global level is statistically challenging (Bolt, van der Aalst, & de Leoni, 2017). ENA can address those issues, as it offers statistical tests and normalizations to compare networks. In turn, process mining indicates the beginning and end points and the cyclical nature of the network.

Combining ENA and process mining provides several affordances. First, it allows us to explore collaboration at both the individual (ENA) and group levels (ENA, process mining). Second, ENA offers statistical procedures to compare regulation patterns of different sizes, which are absent in process mining. Third, combining the methods allows us to study the sequence of regulatory processes (process mining), while accounting for differences in network structures (ENA). The analyses suggest that even if two groups have largely similar frequency counts of codes, they may engage in different sequences and types of regulation.

6.5. Limitations and future research

Several limitations should be taken into consideration. First, the small sample size limits generalization of findings across populations and statistical power to detect a small to moderate effect of team's regulation patterns. In addition, the data were collected from a large, selective public research university with a significant population of underrepresented and first-generation college students. Thus, findings from our student demographic may not be generalizable to other contexts. Future research that employs larger sample sizes may examine potential differences in regulation processes across student groups in more detail. Researchers may also collect student-level characteristics and use experimental designs to explore the causal links between social exchange and regulation patterns, for example, whether there exists a feedback loop where having more diverse strategies results in extended social exchange.

Second, the analyses did not include students' baseline motivation or baseline content knowledge. We were not able to acquire these data

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.learninstruc.2021.101443>.

Appendix. Coding Scheme for Regulatory Processes and Types

because data collection occurred midway through the school year. Future work can account for how baseline characteristics interact with collaboration patterns in project-based learning environments.

Third, this study links students' social exchange within the engineering course to regulatory patterns in the same course. Other researchers have drawn connections between social exchange in the major or at the university to students' self-efficacy and performance (Hurtado, Newman, Tran, & Chang, 2010; Tonso, 2006). Examining the variation in social exchange and regulation in other learning contexts is a potential future direction. In this study, we did not find much overlap between the peers that students mentioned in the social exchange survey and the members of their teams. A possible reason is potential conflict in students' schedules, as the course offered lab sessions during different time slots. Future work can examine the implications for interaction when students self-select into groups with no scheduling constraint.

Finally, as more samples of team discourse are collected, computational linguistics can be applied to automatically code for regulatory processes and types to provide near-real-time feedback for individuals and teams.

7. Conclusions

The current study provides insights into the regulatory patterns and sequences of student discourse in ways that content analyses of code frequencies do not afford. Understanding the link between group-level regulation and students' efficacy is integral to improving the learning experiences for students who generally report a lack of peer interactions. In addition, our study illustrates the use of quantitative discourse analysis approaches, namely ENA and process mining, to analyze student discourse in greater depth. Overall, exploring scaffolds for group-level regulation may promote learning and instruction in engineering and beyond.

CRedit authorship contribution statement

Ha Nguyen: Conceptualization, Methodology, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization. **Kyu Yon Lim:** Conceptualization, Methodology, Formal analysis, Writing - review & editing. **Liang Li Wu:** Investigation, Writing - review & editing. **Christian Fischer:** Supervision, Writing - review & editing. **Mark Warschauer:** Supervision, Funding acquisition.

Acknowledgements

We thank the students who participated in this study, the lab facilitator for helping us set up the recorders, and our research assistants, Pedro Serrano and Dorthy Schmidt for assisting us with checking the transcription quality and coding.

This work is supported by the National Science Foundation #1535300 and the National Research Foundation of Korea, NRF-2017R1A2B4002606. The views contained in this article are those of the authors, and not of the National Science Foundation or the Korean government.

Code	Definition	Example
Processes		
Task understanding	Activate prior knowledge. Discuss instruction. Think about tasks' purpose and value.	Mitchel: There probably is. What was the document that she told us to use where like she showed us oh this is how you communicate between the two? There are sample codes somewhere.
Strategic planning	Discuss available resources. Set timeline. Divide work. State goals to achieve within the current session or long-term goals.	Jake: We just need to connect everything right? Pam: Oh and you need to calibrate the naza. Andy: I can calibrate the naza from 3 to 4. Jake: You want to do it? Honestly, I can give you the naza right now and you can do it at home. Andy: No you can't because you need all the parts. Charlie: I wouldn't try to tighten it too hard because of the screwdrivers. Annie: Yeah no that thing sucks I'm worried.
Motivation	Share feelings and motivation beliefs regarding tasks. Discuss the group's capabilities, strengths, and challenges.	
Control & collaboration	Discuss tasks. Write/build together. Encourage group members. Ask for help from teaching assistants, instructors, or peers.	Mitchel: The best way is to push on the lid at the very end closest to there and push your fingers. Pat: And once we have the latch attached to it. It will be fine. Mitchel: You can push it. I am not looking for a lot, but if you push down onto this and forward then you pull it comes off easily.
Progress monitoring	Praise/evaluate an idea, a solution, or the group's progress regarding goals. Monitor progress regarding time.	Pat: How are we doing over here? Mitchel: We are looking good. Making some bus lines. We are almost done with the circuit that includes the barometer ...
Reflection	Evaluate if the group reached goals. Evaluate how the group solved a task. State what kinds of feelings the overall task aroused. Discuss challenges in the performance.	[After testing the quadcopter] Chris: It was really crazy. Charlie: I didn't record it because I actually was not expecting that. Annie: I just don't know why—what would have caused that. Charlie: last quarter it wasn't the motor. It was just like the direction of the propellers. Did you make sure the propellers are on the right way?
Off-task	Non-course related discussion	I am hungry.
Regulatory Types		
Self-regulate	Individuals ("I" perspective) about task perception, knowledge, goals, motivations.	<i>Example 1.</i> Valerie: Can you repeat that? This is really confusing, actually. <i>Example 2.</i> Chris: I forgot the actual wiring and it really depends on the code which I do have a meeting set up with my friends for. <i>Example 3.</i> Cam: It's actually not too far off, it's actually doable. A lot of it is going to be my battle this weekend with coding.
Shared regulate	"Our" perception of tasks; suggestions; actively constructing knowledge together.	Valerie: So do you guys want to calibrate it today? Annie: Yeah let's start connecting and calibrating stuff. Annie: Wait, so was it, we solder the esc or whatever, is that what we're soldering? Charlie: For some reason, I heard a TA from the open lab say you don't have to solder that. Cam: Yeah they said you don't have to. Annie: So we are not soldering anything? Cam: Yeah we don't have to worry about that yet.

Notes. Student names are pseudonyms.

References

- Ahmed, S., Wallace, K. M., & Blessing, L. T. M. (2003). Understanding the differences between how novice and experienced designers approach design tasks. *Research in Engineering Design, 14*(1), 1–11. <https://doi.org/10.1007/s00163-002-0023-z>
- Alavi, S. B., & McCormick, J. (2008). The roles of perceived task interdependence and group members' interdependence in the development of collective efficacy in university student group contexts. *British Journal of Educational Psychology, 78*(3), 375–393. <https://doi.org/10.1348/000709907X240471>
- Allen-Ramdial, S. A. A., & Campbell, A. G. (2014). Reimagining the pipeline: Advancing STEM diversity, persistence, and success. *BioScience, 64*(7), 612–618.
- Atman, C. J., Cardella, M. E., Turns, J., & Adams, R. (2005). Comparing freshman and senior engineering design processes: An in-depth follow-up study. *Design Studies, 26*(4), 325–357. <https://doi.org/10.1016/j.destud.2004.09.005>
- Bannert, M., Reimann, P., & Sonnenberg, C. (2014). Process mining techniques for analyzing patterns and strategies in students' self-regulated learning. *Metacognition and Learning, 9*(2), 161–185. <https://doi.org/10.1007/s11409-013-9107-6>
- Blau, P. M. (1964). *Exchange and power in social life*. New York: John Wiley.
- Bolt, A., van der Aalst, W. M. P., & de Leoni, M. (2017). Finding process variants in event logs. In *OTM confederated international conferences "on the move to meaningful internet systems"* (pp. 45–52). Springer.
- Cohen, E. G., & Lotan, R. A. (2014). *Designing groupwork: Strategies for the heterogeneous classroom* (3rd ed.). Teachers College Press.
- Creswell, J. W., & Clark, V. L. P. (2017). *Designing and conducting mixed methods research*. Sage publications.
- Cropanzano, R., & Mitchell, M. S. (2005). Social exchange theory: An interdisciplinary review. *Journal of Management, 31*(6), 874–900.
- Curşeu, P. L., & Pluut, H. (2013). Student groups as learning entities: The effect of group diversity and teamwork quality on groups' cognitive complexity. *Studies in Higher Education, 38*(1), 87–103. <https://doi.org/10.1080/03075079.2011.565122>
- Dawson, S. (2008). A study of the relationship between student social networks and sense of community. *Journal of Educational Technology & Society, 11*(3), 224–238. Retrieved from <http://www.jstor.org/stable/jeductechsoci.11.3.224>.
- De Backer, L., Van Keer, H., & Valcke, M. (2015). Exploring evolutions in reciprocal peer tutoring groups' socially shared metacognitive regulation and identifying its metacognitive correlates. *Learning and Instruction, 38*, 63–78. <https://doi.org/10.1016/j.learninstruc.2015.04.001>
- Eagan, K., Hurtado, S., Figueroa, T., & Hughes, B. E. (2014). *Examining STEM pathways among students who begin college at four-year institutions*. National Academy of Sciences.
- Emerson, R. M. (1976). Social exchange theory. *Annual Review of Sociology, 2*(1), 335–362.
- Engelmann, K., & Bannert, M. (2019). *Analyzing temporal data for understanding the learning process induced by metacognitive prompts*. Learning and Instruction, 101205.
- Falk, I., Dym, C. L., Agogino, A. M., Frey, D. D., Leifer, L. J., Now, C., et al. (2014). Design thinking: A unified framework for innovation. *Journal of Engineering Education, 41*(3), 1–5. <https://doi.org/10.1002/j.2168-9830.2005.tb00832.x>
- Galand, B., Raucant, B., & Frenay, M. (2010). Engineering students' self-regulation, study strategies, and motivational beliefs in traditional and problem-based curricula. *International Journal of Engineering Education, 26*(3), 523–534.
- Gašević, D., Adesope, O., Joksimović, S., & Kovanović, V. (2015). Externally-facilitated regulation scaffolding and role assignment to develop cognitive presence in asynchronous online discussions. *Internet and Higher Education, 24*, 53–65. <https://doi.org/10.1016/j.iheduc.2014.09.006>
- Gašević, D., Joksimović, S., Eagan, B. R., & Shaffer, D. W. (2019). Sens: Network analytics to combine social and cognitive perspectives of collaborative learning. *Computers in Human Behavior, 92*, 562–577. <https://doi.org/10.1016/j.chb.2018.07.003>
- Gibson, C. B. (2001). From knowledge accumulation to accommodation: Cycles of collective cognition in work groups. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior, 22*(2), 121–134.
- Hadwin, A. F. (2019). *Commentary and future directions: What can multi-modal data reveal about temporal and adaptive processes in self-regulated learning?* Learning and Instruction, 101287.

- Hadwin, A. F., Järvelä, S., & Miller, M. (2011). Self-regulated, co-regulated, and socially shared regulation of learning. *Handbook of Self-Regulation of Learning and Performance*, 30, 65–84.
- Hatamura, Y. (Ed.). (2006). *Decision-making in engineering design*. <https://doi.org/10.1007/1-84628-261-6>
- Homans. (1961). *Social behavior: Its elementary forms*. New York: Harcourt, Brace.
- Hurtado, S., Newman, C. B., Tran, M. C., & Chang, M. J. (2010). Improving the rate of success for underrepresented racial minorities in STEM fields: Insights from a national project. *New Directions for Institutional Research*, 2010(148), 5–15. <https://doi.org/10.1002/ir.357>
- Janssenswillen, G., Depaire, B., Swennen, M., Jans, M., & Vanhoof, K. (2019). bupaR: Enabling reproducible business process analysis. *Knowledge-Based Systems*, 163, 927–930.
- Järvelä, S., & Hadwin, A. F. (2013). New frontiers: Regulating learning in CSCL. *Educational Psychologist*, 48(1), 25–39.
- Järvelä, S., Järvenoja, H., & Malmberg, J. (2019). Capturing the dynamic and cyclical nature of regulation: Methodological progress in understanding socially shared regulation in learning. *International Journal of Computer-Supported Collaborative Learning*, 14(4), 425–441.
- Järvelä, S., Kirschner, P. A., Hadwin, A., Järvenoja, H., Malmberg, J., Miller, M., et al. (2016a). Socially shared regulation of learning in CSCL: Understanding and prompting individual- and group-level shared regulatory activities. *International Journal of Computer-Supported Collaborative Learning*, 11(3), 263–280.
- Järvelä, S., Kirschner, P. A., Panadero, E., Malmberg, J., Phielix, C., Jaspers, J., et al. (2015). Enhancing socially shared regulation in collaborative learning groups: Designing for CSCL regulation tools. *Educational Technology Research & Development*, 63(1), 125–142.
- Järvelä, S., Malmberg, J., & Koivuniemi, M. (2016b). Recognizing socially shared regulation by using the temporal sequences of online chat and logs in CSCL. *Learning and Instruction*, 42, 1–11.
- Järvenoja, H., Järvelä, S., & Malmberg, J. (2015). Understanding regulated learning in situative and contextual frameworks. *Educational Psychologist*, 50(3), 204–219.
- Järvenoja, H., Järvelä, S., Törmänen, T., Näykki, P., Malmberg, J., Kurki, K., et al. (2018). Capturing motivation and emotion regulation during a learning process. *Frontline Learning Research*, 6(3), 85–104.
- Jermann, P., & Dillenbourg, P. (2008). Group mirrors to support interaction regulation in collaborative problem solving. *Computers & Education*, 51(1), 279–296.
- Jones, B. D., Paretto, M. C., Hein, S. F., & Knott, T. W. (2010). An analysis of motivation constructs with first-year engineering students: Relationships among expectancies, values, achievement, and career plans. *Journal of Engineering Education*, 99(4), 319–336. <https://doi.org/10.1002/j.2168-9830.2010.tb01066.x>
- Kapur, M., Voiklis, J., & Kinzer, C. K. (2008). Sensitivities to early exchange in synchronous computer-supported collaborative learning (CSCL) groups. *Computers & Education*, 51(1), 54–66.
- Krajcik, J., McNeill, K. L., & Reiser, B. J. (2008). Learning-goals-driven design model: Developing curriculum materials that align with national standards and incorporate project-based pedagogy. *Science Education*, 92(1), 1–32.
- Kwon, K., Liu, Y. H., & Johnson, L. P. (2014). Group regulation and social-emotional interactions observed in computer supported collaborative learning: Comparison between good vs. poor collaborators. *Computers & Education*, 78, 185–200.
- Malmberg, J., Järvelä, S., & Järvenoja, H. (2017). Capturing temporal and sequential patterns of self-, co-, and socially shared regulation in the context of collaborative learning. *Contemporary Educational Psychology*, 49, 160–174. <https://doi.org/10.1016/j.cedpsych.2017.01.009>
- Marquart, C. L., Hinojosa, C., Swiecki, Z., Eagan, B., & Shaffer, D. W. (2018). *Epistemic network analysis (version 1.5. 2)[software]*.
- Melzner, N., Greisel, M., Dresel, M., & Kollar, I. (2019). Using process mining (PM) and epistemic network analysis (ENA) for comparing processes of collaborative problem regulation. In *International conference on quantitative ethnography* (pp. 154–164). Springer.
- Melzner, N., Greisel, M., Dresel, M., & Kollar, I. (2020). Regulating self-organized collaborative learning: The importance of homogeneous problem perception, immediacy and intensity of strategy use. *International Journal of Computer-Supported Collaborative Learning*, 15(2), 149–177.
- Miller, M., & Hadwin, A. (2015). Scripting and awareness tools for regulating collaborative learning: Changing the landscape of support in CSCL. *Computers in Human Behavior*, 52, 573–588.
- Mills, J. E., & Treagust, D. F. (2003). Engineering education—is problem-based or project-based learning the answer. *Australasian Journal of Engineering Education*, 3(2), 2–16.
- Molenaar, I., & Chiu, M. M. (2014). Dissecting sequences of regulation and cognition: Statistical discourse analysis of primary school children's collaborative learning. *Metacognition and Learning*, 9(2), 137–160. <https://doi.org/10.1007/s11409-013-9105-8>
- Nguyen, H., Wu, L., Fischer, C., Washington, G., & Warschauer, M. (2020). Increasing success in college: Examining the impact of a project-based introductory engineering course. *Journal of Engineering Education*, 109(3), 384–401. <https://doi.org/10.1002/jee.20319>
- Pintrich, P. R. (2000). Multiple goals, multiple pathways: The role of goal orientation in learning and achievement. *Journal of Educational Psychology*, 92(3), 544.
- Purzer, Ş. (2011). The relationship between team discourse, self-efficacy, and individual achievement: A sequential mixed-methods study. *Journal of Engineering Education*, 100(4), 655–679. <https://doi.org/10.1002/j.2168-9830.2011.tb00031.x>
- Putnik, G., Costa, E., Alves, C., Castro, H., Varela, L., & Shah, V. (2016). Analysing the correlation between social network analysis measures and performance of students in social network-based engineering education. *International Journal of Technology and Design Education*, 26(3), 413–437. <https://doi.org/10.1007/s10798-015-9318-z>
- R Core Team. (2019). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. URL <https://www.R-project.org/>.
- Rogat, T. K., & Linnenbrink-Garcia, L. (2011). Socially shared regulation in collaborative groups: An analysis of the interplay between quality of social regulation and group processes. *Cognition and Instruction*, 29(4), 375–415.
- Romero, C., Ventura, S., Pechenizkiy, M., & Baker, R. S. (2010). *Handbook of educational data mining*. CRC press.
- Shaffer, D. W. (2017). *Quantitative ethnography*. Madison, WI: Cathcart Press.
- Shaffer, D. W., Collier, W., & Ruis, A. R. (2016). A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics*, 3(3), 9–45.
- Sha, L., & van Aalst, J. (2003, April). An application of social network analysis to knowledge building. In *Annual meeting of the American educational research association* (pp. 21–25).
- Stefanou, C., Stolk, J. D., Prince, M., Chen, J. C., & Lord, S. M. (2013). Self-regulation and autonomy in problem- and project-based learning environments. *Active Learning in Higher Education*, 14(2), 109–122. <https://doi.org/10.1177/1469787413481132>
- Stribos, J. W., Martens, R. L., Prins, F. J., & Jochems, W. M. G. (2006). Content analysis: What are they talking about? *Computers & Education*, 46(1), 29–48. <https://doi.org/10.1016/j.compedu.2005.04.002>
- Tonso, K. L. (2006). Teams that work: Campus culture, engineer identity, and social interactions. *Journal of Engineering Education*, 95(1), 25–37. <https://doi.org/10.1002/j.2168-9830.2006.tb00875.x>
- Ucan, S., & Webb, M. (2015). Social regulation of learning during collaborative inquiry learning in science: How does it emerge and what are its functions? *International Journal of Science Education*, 37(15), 2503–2532. <https://doi.org/10.1080/09500693.2015.1083634>
- Volet, S., Vauras, M., & Salonen, P. (2009). Self- and social regulation in learning contexts: An integrative perspective. *Educational Psychologist*, 44(4), 215–226.
- Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge University Press.
- Wellman, B., & Wortley, S. (1990). Different strokes from different folks: Community ties and social support. *American Journal of Sociology*, 96(3), 558–588.
- Wu, L. L., Fischer, C., Rodriguez, F., & Washington, G. (2018). Evaluation of online learning in a first-year engineering design course. In *Proceedings of the American Society for Engineering Education Annual Conference, Salt Lake City, UT*.
- Yan, Z., Wang, T., Chen, Y., & Zhang, H. (2016). Knowledge sharing in online health communities: A social exchange theory perspective. *Information & Management*, 53(5), 643–653.
- Zheng, L. (2017). A socially shared regulation approach to improving group cohesion, collective efficacy, and regulation skills in CSCL. In *Knowledge building and regulation in computer-supported collaborative learning* (pp. 83–96). Singapore: Springer.
- Zheng, J., Xing, W., & Zhu, G. (2019). Examining sequential patterns of self- and socially shared regulation of STEM learning in a CSCL environment. *Computers & Education*, 136, 34–48. <https://doi.org/10.1016/j.compedu.2019.03.005>
- Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In *Handbook of self-regulation* (pp. 13–39). Academic Press.
- Zimmerman, B. J., & Kitsantas, A. (2005). The hidden dimension of personal competence: Self-regulated learning and practice. In A. J. Elliot, & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 509–526). Guilford Publications.
- Zimmerman, B. J., & Schunk, D. H. (2011). *Handbook of self-regulation of learning and performance*. Routledge/Taylor & Francis Group.