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Exploring the influence of regulated learning processes on learners' prestige in project-based learning

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Abstract

With the development of information and communication technology, project-based learning (PBL) has become an important pedagogical approach. Group leaders are critical in PBL, and prestige influences learner leadership. Regulation affects learners' prestige, but research on their relationship is lacking. Through content analysis and epistemic network analysis, we examine the regulatory patterns of 21 learners engaged in multi-layered online PBL through online collaborative learning activities over 14 weeks. The analysis results show that: (1) High-prestige learners engaged significantly in "socially shared regulation ($U = 24.0$, $Z = -2.183$, $p = 0.029$)", "monitoring ($U = 26.5$, $Z = -2.008$, $P = 0.043$)", "task understanding ($U = 15.0$, $Z = -2.829$, $p = 0.004$)", and "organizing O ($U = 20.5$, $Z = 0.015$, $p = 0.013$)". (2) The regulatory patterns during PBL stages show that high-prestige learners focus on task dimensions in intra-group discussions. (3) High-prestige learners display positive emotions in inter-group assessments and intra-group refinements. In contrast, low-prestige learners exhibit higher negative emotional engagement. (4) There is a strong correlation between socially shared regulation ($GRG = 0.780$), content monitoring ($GRG = 0.728$), and learners' prestige. Socially shared regulation ($p = 0.001$), self-regulation ($p = 0.001$), monitoring ($p = 0.006$), evaluation ($p = 0.019$), content monitoring ($p = 0.000$), and process monitoring ($p = 0.018$) all significantly positively impact learners' prestige. The findings suggest that providing self-regulation and socially shared regulation scaffolding for PBL and utilizing various other methods to enhance learner regulation of learning are likely to increase learners' prestige and PBL effectiveness.

Keywords PBL · Regulation · Prestige · Learning analysis

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1 Introduction

Prestige serves as a reflection of learners' leadership capabilities and exerts an influential role in their overall leadership in learning contexts. High-prestige learners play a crucial role, holding the highest discourse status within the team. They are often recognized as opinion leaders or hotshots and hold a crucial role in group discussions and open forums (Li et al., 2013; Greimel et al., 2023). Prestige influences the social presence and the process and outcomes of team collaboration (Neely Jr et al., 2020; Zou et al., 2021).

Effective regulation of the learning process is key to ensuring the efficiency and quality of project-based learning (PBL). Previous studies have indicated that successful collaboration cannot be separated from learners' self-regulation (SR), co-regulation (CoR), and socially shared regulation (SSR) (Järvelä et al., 2013). SR is crucial for successful learning, which refers to learners' planning, monitoring, regulating, and evaluating their learning process (Dignath & Büttner, 2008). CoR is the process of coordinating and monitoring the cognitive, metacognitive, motivational, and affective aspects of learning among learners with each other. SSR is the process where all members work together to coordinate their learning, and it requires all members to participate and work together to achieve the group's goals. How SR, CoR, and SSR work together to create successful learning is also a focus of current research (Järvelä et al., 2019). PBL goes beyond the SR of individual members. It requires members to share cognitive processes and co-regulate the learning process. There is a great deal of interactive behavior among a team when completing a task. At the same time, the learner's activities, choices, and outcomes are intertwined with the dynamics of personal, social, and environmental conditions (Järvelä et al., 2016a; Shaffer et al., 2016). Thus, the online PBL process generates more complex and multifaceted cognitive, motivational, and affective challenges than the individual learning process (Miyake & Kirschner, 2014). Learners' online collaborative session data can reflect learners' cognitive processes and social interaction states. Accordingly, understanding learners' learning states in PBL can inform personalized feedback and teacher interventions.

Project-based learning (PBL) is a learning model that has the potential to significantly improve students' learning outcomes, positively contributing to academic achievement, affective attitudes, and thinking skills (De Oliveira Biazus & Mahtari, 2022; Hamad et al., 2022; Karpudewan et al., 2016; Zhang & Ma, 2023). However, successful implementation of PBL is not an easy task, as it requires team members to work together to complete real-world and meaningful projects. Learners need to formulate the team's task objectives, plan, monitor, regulate, and evaluate the entire process to solve problems, resolve conflicts, and achieve the goals successfully (Chen & Yang, 2019). Studies have shown that collaborative PBL works better than traditional PBL (Cheng & Yang, 2023; Zhang & Ma, 2023). Therefore, we adopt the Funnel Model based on collaborative learning (Wen et al., 2011; Wen, 2019; Zhang et al., 2021) to divide collaborative PBL into three stages: intra-group discussion, inter-group assessment, and intra-group refinement. Through this approach, we expect to systematically cultivate students' regulation skills, critical thinking, and problem-solving abilities, thereby achieving higher learning prestige and educational value.

It is important to note that a learner's performance in regulated learning is directly related to their prestige level. The main objective of this study is to explore in-depth regulatory behavior and its impact on learners' prestige in PBL. That leads to the following research questions:

1. What are the differences in the regulated learning patterns of high- and low-prestige learners?
2. What are the differences between high- and low-prestige learners in the three stages of PBL?
3. How does regulatory behavior affect learners' prestige?

This paper sorts out the indegree and LeaderRank as indicators to measure learners' prestige through literature and realizes the calculation of relevant algorithms through Python. Statistical analysis, content analysis, and epistemic network analysis (ENA) are used to discover the regulated learning patterns of high-prestige learners and low-prestige learners in PBL. We use grey correlation analysis to determine which factors are associated with the learner's prestige and stepwise regression analysis to determine which specific dimensions can predict the learner's prestige. Results indicated that high-prestige learners exhibited socially shared regulation and demonstrated numerous regulatory behaviors in task understanding and organization. This paper also revealed substantial regulatory behaviors in monitoring and task management by identifying and comparing the regulatory patterns of high- and low-prestige learners.

The article's contributions are summarized as follows:

- We introduce practical PBL activities tailored to database courses, providing a valuable pedagogical framework for instructors of artificial intelligence technology courses.
- We quantify the prestige of each group member using the LeadRank algorithm. The application of the LeadRank algorithm represents a tangible integration of information and communication technology in education.
- We uncover distinct regulatory behavioral patterns between high- and low-prestige learners, revealing an association between regulatory behavior and prestige levels, which guides (1) educators to offer personalized guidance aligned with learners' prestige and (2) learners to adapt their team and individual tasks in response to their prestige feedback.

The rest of the paper is organized as follows: Section 2 reviews the existing research on regulated learning and learners' prestige. Section 3 introduces the research design, participants, data collecting and data analysis. Section 4 presents the differences in regulatory learning processes of learners with different prestige by ENA. Section 5 explored regulatory behavior and how it affects learners' prestige by grey correlation and step-wise regression analysis. In section 6, we further discuss the results and implications of this study. Section 7 concludes the paper and explores the potential directions for future work.

2 Related work

This section explores the relationship between regulatory behaviors and the learner's prestige in PBL. PBL is the context. Regulated learning and learners' prestige are the main concepts. Therefore, the related literature reviewed is regarding three aspects: (1) learners' prestige, (2) regulation of learning, and (3) PBL.

2.1 Learners' prestige

Social network analysis has become a popular computational approach for exploring online learning interactions. According to Borgatti et al. (2009), it examines a social network as a collection of entities (usually referred to as actors or nodes) connected by a relationship (often referred to as an edge or link). In this context, learners' prestige can be defined as a measure of how valuable the information an individual provides and how important his or her connections are (Zou et al., 2021). The level of an individual's connections, measured by degree centrality, captures their prestige in a social network by considering the number and quality of their relationships. Degree centralities, known as local centralities, are measures of direct interactions or local contacts between actors. The most used degree centrality measures are indegree centrality and outdegree centrality (Saqr et al., 2022; Liang et al., 2024). In online learning, especially computer support collaboration learning (CSCL) and Project-based learning (PBL), it is usually calculated as the number of messages, posts, comments, or contacts a learner makes or receives. Indegree centrality, also referred to as prestige centrality, quantifies the total number of connections or interactions a node receives from other nodes (Dowell et al., 2015; Marcos-García et al., 2015; Liao et al., 2017; Borgatti & Brass, 2019). In online learning, this metric is typically calculated based on the number of replies or comments a user receives. It serves as an indicator of popularity, influence, and prestige (Han et al., 2021; Wu & Wu, 2021; Liu et al., 2022; Li & Sharma, 2023; Wei et al., 2024; Duan et al., 2024). Additionally, indegree centrality reflects the perceived value or worthiness of an actor's contributions, assuming replies are given when contributions are considered valuable, useful, or contentious. Algorithms, such as the HITS algorithm (Kleinberg, 1999), the PageRank algorithm (Page, 1998), and the LeaderRank (Lü et al., 2011), have been used to measure an individual's prestige. Among them, the HITS algorithm and PageRank algorithm are suitable for open social networks, such as MOOCs. They are not suitable for network structures consisting of disconnected subnetworks (Rosé, 2017), such as the group in CSCL and PBL. However, the LeaderRank algorithm can solve this dilemma. Thus, this study uses indegree centrality and LeaderRank to measure learners' prestige.

Posts or messages from high-prestige learners can attract more responses. This popularity can translate into leadership capabilities as others are more likely to follow or be influenced by this individual's actions and decisions (Balkundi & Kilduff, 2006; Sparrowe & Kraimer, 2024; Mehra et al., 2006). High-prestige learners can lead group members to actively participate in collaborative exchanges, share ideas, facilitate in-depth discussions, and oversee the collaborative process. High-prestige learners often act as communication hubs, receiving and disseminating information efficiently. This central position allows them to guide the entire group into active participation by fostering collaborative dialogue, sharing ideas, facilitating in-depth discussions, and overseeing the collective learning process (Saqr et al., 2022). High-prestige learners possess essential leadership skills, such as the ability to mediate, regulate, and resolve collaborative conflicts, which advance the group's shared learning objectives and promote socially shared regulated learning (SSR) within the group. They are responsible for assigning tasks, coordinating group projects, and managing the group's decision-making processes. By leading group members in active participation, sharing ideas, facilitating in-depth discussions, and overseeing the collaborative process, high-prestige learners excel in achieving the group's shared learning objectives and fostering SSR (Oh et al., 2018). Ouyang and Dai (2022) investigated social participation roles as critical indicators of cognitive participation levels and found that high-prestige learners make substantial contributions to knowledge inquiry and knowledge building, surpassing low-prestige learners.

2.2 Regulation of learning

Regulation of learning is a cyclical and intricate metacognitive and social phenomenon encompassing the monitoring and control of cognitive, motivational, emotional, and behavioral aspects (Boekaerts, 1996; Hacker et al., 1998; Hadwin et al., 2017; Järvelä & Hadwin, 2013; Su et al., 2018). Regulation of learning evolved from the earlier theory of self-regulated learning (Shaffer et al., 2016). Individual regulation of learning is important because it represents the regulatory role of individual members, including their perceptions, metacognitive reflections, and interpretations. Regulation of learning in groups contributes to understanding the conditions of social construction and motivation formation (Järvelä & Järvenoja, 2011). According to Järvenoja and Järvelä (2009), self-regulated learning involves a dual interaction between the individual and the social context. It entails integration as a personal characteristic into social, shared, and interactive learning processes. Individual members function as interdependent self-regulated entities within a group, forming a cohesive social structure. This confluence of groups and individuals presents both opportunities and challenges.

In the regulation of learning, there are three regulatory types; namely, self-regulation (SR), co-regulation (CoR), and socially shared regulation (SSR) (Schunk & Zimmerman, 2012; Winne et al., 2013). SR involves setting goals, choosing strategies, and monitoring one's own learning process, encompassing cognitive, metacognitive, motivational, affective, and behavioral aspects (Schunk & Zimmerman, 2012). SR is used both in individual and collaborative learning, playing a crucial role in successful collaboration (Winne et al., 2013; Winters & Alexander, 2011). CoR refers to how an individual's cognitive, metacognitive, motivation and emotional processes adapt to the influence, guidance, support, and constraints imposed by others (Hadwin & Oshige, 2011). CoR primarily happens during interactions among individuals and emphasizes inter-individual influences. SSR is a process where a group collectively negotiates and regulates cognition, behavior, motivation, and emotion as a unified entity (Bandura, 1997; Järvelä et al., 2016b). SSR involves setting goals, overseeing the learning process, and engaging in discussions to reach a consensus. SSR plays a central role in effective collaborative learning (Hadwin et al., 2017). These regulatory types coexist in collaborative learning and are interconnected and mutually reinforcing. According to Su et al. (2018), SSR and CoR can happen as a group moves through several phases of cooperation; however, they don't always happen independently.

During the regulation of learning, learners begin with clear learning objectives. Learners possess the capacity to monitor and regulate a spectrum of cognitive, motivational, behavioral, and environmental elements (Winne, 2013; Zimmerman, 1989, 2000). Concurrently, learners self-evaluate their behavior (Winne & Perry, 2000). The focal object of evaluation for learners is that they engage in regulatory processes. It encompasses five critical facets: cognition, behavior, metacognition, emotion, and motivation. In practical implementation, the regulation focus is usually divided into task, emotion, and organization (Su et al., 2018; Zheng et al., 2019; Zhang et al., 2021).

2.3 Project-based learning and computer-supported collaborative learning

Project-based learning (PBL) is an inquiry-based model that uses various resources to conduct continuous real-world activities, focusing on subject concepts, principles, and results within a specific timeframe (Oliveira, 2023). Zhang and Ma (2023) noticed that PBL worked better in lab classes than in theory lectures, such as engineering and technology fields. Meanwhile, PBL is also more effective when integrated with collaborative group learning. The best results were obtained in groups of 4-5 students. The PBL model can improve individual and group performance while enhancing understanding of group (Maros et al., 2023). In this study, we research PBL practices at the course level (Chen et al., 2021). We encouraged learners to collaborate within groups, addressing real-life challenges and producing meaningful artifacts. Successful implementation of PBL requires guidance from the instructional design.

Computer-Supported Collaborative Learning (CSCL) is a pedagogical approach that uses computers and networked devices to facilitate synchronous or asynchronous collaboration among learners either remotely or in face-to-face settings (Dillenbourg et al., 2009; Stahl et al., 2014). CSCL provides learners with opportunities for engaging in joint tasks, rich communication through various modes, sharing and organizing resources, structured collaboration, co-constructing knowledge, and building community relationships (Cao et al., 2022; Serrano-Cámara et al., 2014; Schoor & Bannert, 2011). However, it requires careful design and monitoring for successful outcomes (Jeong & Hmelo-Silver, 2016; Rienties et al., 2020).

In summary, SSR has witnessed a growing body of literature, with a particular focus on regulatory behaviors among diverse performance groups and across various cultural backgrounds. Typically, research in this domain tends to focus on disparities while overlooking the distinctive attributes of subgroups that emerged within a group as the result of member interactions. We undertake a detailed description of the regulatory behaviors within distinct prestige learners that emerge as a result of online discussions within groups. We use the LeaderRank algorithm to calculate the learners' prestige. We also employ data mining techniques, including ENA and CA. Additionally, we apply gray correlation and regression analysis to explore and elucidate the relationship between group prestige and the regulatory behavior exhibited within these groups.

3 Methodology

This study explores the relationship between regulated learning and learners' prestige in PBL. We provide an overview of the collaborative activity design derived from database courses. Additionally, we discuss the coding schemes of regulatory types, processes, and foci. For learners' prestige, we introduce how to label learners' discourse and how to use the LeaderRank algorithm to calculate different prestige.

3.1 Learning tasks and PBL activity designs

The course, *Database and its Principles*, is a mandatory component within the curriculum for educational technology majors. It is a foundational course that precedes advanced courses like *Website Design and Development* and *Web Development and Application*. Considering the real-world educational environment and research requirements, we chose a blended teaching style that blends online and offline approaches. This approach ensures learners acquire the theoretical knowledge and practical skills to understand and develop databases. Offline activities focus on theoretical comprehension and code exercises, whereas online activities are designed for collaborative learning activities that allow students to apply their knowledge to practical issues. CSCL activities script designed based on the Funnel Model (Wen et al., 2011; Wen, 2019; Zhang et al., 2021), which consists of three stages of multilayered interactions for continuous knowledge construction. This model has been demonstrated to enhance learners' participation and interaction in CSCL. The design and development of database systems involve six stages: the requirements analysis, the conceptual design, the logical design, the physical design, the database implementation, and the database operation and maintenance. Based on the actual conditions of database system development, this study implements PBL practices at the course level (Chen et al., 2021). Throughout the 14 weeks of data collection, learners form groups of 4-5 people and work together to develop a database system based on a self-defined topic (Zhang & Ma, 2023). Students are required to form their groups and submit their group lists on the Xiaoya platform, the online learning platform. Table 1 displays the weekly tasks. Each week, group tasks are assigned, and at the end of the course, each group produces a final database system design and code. Weekly group tasks require the participation of all members, and the group needs to review and discuss the assignments before submission. The designed framework integrates stages tailored to the database development process, as shown in Fig. 1. The green rectangles represent the PBL group activities, and the blue rectangles represent the database development process.

1. Stage 1: Intra-group discussion stage (the yellow rectangle on the left in Fig. 1). Group members begin the process by generating their own opinions. Within the group, learners actively discuss and exchange ideas (green color). At this stage,

Table 1 The process of online PBL activity

Stage	Weeks	Group assignments
Intra-group	1	Create subgroups to identify database system issues.
discussion (S1)	2	Requirement collection and analysis: Obtain the user's information requirements, processing requirements, and security and integrity requirements for the database through research, collection, and analysis.
	3	Conceptual database design: Complete the conceptual model (E-R model) design and data dictionary determination.
	4-5	Logical database design: Finish the conversion of the E-R model to a relational model using logical database design.
Inter-group assessment (S2)	6	Distribute and report on the group's database documents (requirement collection and analysis, E-R model, and relational model) and analyze the designs of other groups.
	7	Create the primary key, the foreign key, and the base tables using SQL statements.
Intra-group refinement	8	Based on feedback suggestions, modify the base tables and build ten most commonly used queries.
(S3)	9	Use SQL statements to create appropriate indexes for the database and explain why.
	10	Create five or more views and describe their job and importance.
	11	Create proper security and identify potential users and permissions.
	12	Check whether database conforms to the third normal form.
	13	Check the database and improve the database design documentation.
	14	Refine the database design documentation and turn it in.

the learners should determine the theme of the database, conduct requirements collection and analysis, craft an entity-relationship (E-R) model, and design the base table for the group's database.

2. Stage 2: Inter-group assessment stage. Group members are expected to thoroughly examine, discuss, and evaluate other groups' documents until a unified opinion is reached. These recommendations will be sent to the evaluated group. After the evaluated group receives the feedback, it discusses within the group whether to accept the feedback suggestions. The evaluated group modifies their databases based on feedback suggestions (the green rectangle in Fig. 1).
3. Stage 3: Intra-group refinement stage (the yellow rectangle on the right in Fig. 1). Group members decide whether or not to incorporate peer feedback and develop database systems based on modified design documents. This stage involves the application of SQL statements for tasks, such as base table modification, index creation and deletion, utilization of subquery-based SELECT statements, and the

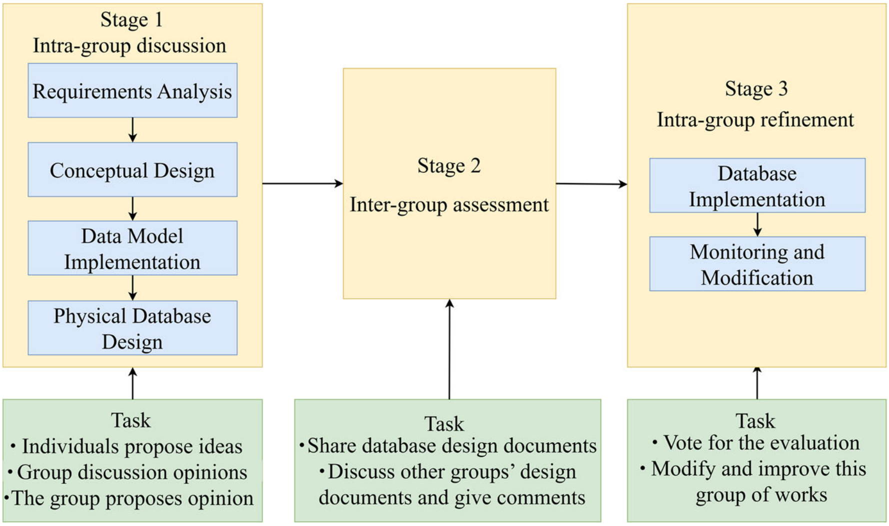

Fig. 1 Process of PBL based on the funnel model

creation and application of views and database constraints. This course's structured approach promotes a dynamic learning experience.

Table 1 displays weekly tasks. Each week, group tasks are assigned, and at the end of the course, each group produces the final database system design manual and code. Throughout the 14 weeks of data gathering, learners create groups of 4-5 people and work together to develop a database system centered on a self-defined topic (Zhang & Ma, 2023).

3.2 Participants

We recruited 21 undergraduate learners majoring in educational technology from the class of 2020 at a top university in China. Among them, there were 15 females and 6 males. Data was collected during the period when the learners took the course *Database and Principles* in Spring 2022. All participants provided informed consent before their inclusion in the study. They were informed about the purpose of the research, the nature of their involvement, and their right to withdraw at any time without any consequences. Participants' anonymity and confidentiality were strictly maintained throughout the research process. Participants mentioned in this study have been anonymized.

3.3 Data collection

In this section, we introduce three important schemes: regulatory types, processes, and focus. We use this scheme as a tool to analyze the learners' discourse from online collaborative PBL activities. We also show how to label reply rules so that the indegree centrality can be calculated.

3.3.1 Coding schemes of regulation

To investigate the regulatory patterns in PBL, student discourse data is collected from the QQ platform and three coding schemes are used to analyze each student's regulatory types, processes, and focus. Table 2 provides codes, definitions, and illustrative examples to demonstrate the rigor and consistency of the coding process (Su et al., 2018; Zhang et al., 2021).

We exported and preprocessed the discourse data from each group on the QQ platform, converting it into Excel files using Python. Two graduate learners in educational technology, having received training on the coding scheme, independently coded 15% of the selected QQ discourse data (Lee et al., 2015). Inter-rater reliability for regulatory type, process, and focus coding was assessed using Cohen's kappa values. The resulting values were 0.897, 0.835, and 0.830, respectively. In general, stability is defined as a kappa of 0.8. Therefore, Cohen's kappa values are found to be acceptable (Carletta, 1996). Coders discussed and negotiated any inconsistent records during coding until an agreement was reached. Then, a single coder completed the coding of the remaining data.

3.3.2 Learners' prestige

Learners' prestige was implemented using the LeaderRank algorithm within a network of QQ group responses. Discourse data was collected over 14 weeks in the *Database and Principles* course. The specific workflow for determining learner prestige is as follows:

1. **Data Collection:** After receiving secured permissions, discussion data was collected from each group on the QQ platform from February 23, 2022, to June 1, 2022. There are a total of 4,075 messages.
2. **Label the Replies:** The replies tend to be less explicit compared to those in more structured online forums. Therefore, the labeling process strictly adhered to the IRC dataset labeling rules and reply coding guidelines [1]. Detailed annotation rules are provided in Table 3. We combined Cohen's kappa to measure the agreement. Overall, we reached an inter-annotator agreement of Cohen's kappa = 0.899. The agreement is quite good, considering the number of categories. The remaining data were labeled by a single annotator.
3. **Construct Response Matrix:** A response matrix for the first group was constructed based on the tagged reply relationships.

[1] http://irclogs.ubuntu.com/

Table 2 The schemes of regulation

	Code	Definition	Example
Regulatory types	Self-regulation (SR)	A learner regulates their behavior, cognition, motivation, or emotion without apparent intentions to influence others' learning.	*I think there is something wrong with my evaluation form.*
	Co-regulation (CoR)	Learners affect others' behavior, cognition, motivation, or emotion.	*@X @ X Where is this task posted?*
	Socially shared regulation (SSR)	Learners' regulatory behaviors are mainly directed to the planning, monitoring, and regulating of joint activity.	*Everyone double-checks to see if anything is missing.*
Regulatory process	Planning (P)	Decision making or preliminary arrangement for the learning task.	*I'll divide it up, about 3 tables each.*
	Monitoring (M)	Learners aware and monitor behavioral, cognitive, motivational, and emotional states.	*Have you all confirmed that every part has been changed?*
	Regulating (R)	After monitoring, learners select and use various cognitive strategies to ensure the completion of the learning task.	*I divided the entry/exit time of the last storage table into two attributes, entry and exit.*
	Evaluating (E)	Learners' judgment, ascertainment, or evaluation attributions of their learning performance.	*I think it is better to do requirement analysis point by point, other things should be written inside the table to make it correct, and the table structure should be done in English to comply with the specification.*
Regulatory focus	Task understanding (TU)	Learners discuss their understanding of the goals and requirements of learning tasks.	*I've put together a little bit of the basics of drawing, combining information from the textbook and online. Do we have to write detailed instructions?*
	Content monitoring (CM)	Learners discuss the contents of database system development.	*For phone numbers, we only need to write them in the form of number + number.*
	Process monitoring (PM)	Learners discuss the progress of their learning tasks or time management.	*You can test the whole thing out by tonight.*

Table 2 continued

Code	Definition	Example
Positive emotion (PE)	Learners are aware of positive emotional or motivating experiences in PBL activities.	*Minds abruptly opened up. A, you are my god!!! hahahahahahahahahahahahahaha, a high-end enterprise.*
Negative emotion (NE)	Learners are aware of negative emotional or motivational experiences in the learning tasks. This may make others upset and impede the pace of learning tasks.	*Isn't it (discussion) at 9pm? I just got up.*
Joking (J)	Learners use emoticons or graphic emotions to regulate the atmosphere of a group.	 
Organizing (O)	Learners talk about the organizing of the learning tasks.	*I'll divide up the tasks, pretty much around 3 tables each. A.1-2 B.3-5 C.6 8 D.9 11+13 E.14 15. Let us each choose one to do.*

Table 3 QQ group reply labeling rules

Number	Rules	Results
1	Learner A sends a message without replying to any message, which means a new conversation is started.	There is invalid response data. It is not included in the analysis.
2	Learner A talks about topics unrelated to learning (i.e., noise messages).	There is invalid response data. It is not included in the analysis.
3	Learner A sends a message to @B or with B's name.	Learner A sends a message to learner B, counting one time.
4	Learner A sends a message without @B or with B's name. However, it is clear from the context that it is a reply to learner B.	Learner A sends a message to learner B, counting one time.
5	Learner A sends multiple messages in a row, replying to learner B's n messages.	Learner A sends messages to learner B, counting n times.
6	Learner A sends repeated messages in succession in response to learner B. For example: *Homework is due tomorrow! Hand in your homework tomorrow! Hand in your homework tomorrow!*	Learner A sends a message to learner B, counting one time.

4. **Calculate Indegree Centrality:** The response matrix was imported into Gephi 2[2], a network analysis and visualization tool, to calculate the indegree centrality of each learner, indicating their level of activity and influence in receiving replies.
5. **Calculate LeaderRank:** We Use Python 3.93[3] to calculate the LeaderRank value for each learner. LeaderRank is a ranking algorithm that evaluates the importance of nodes in the network and is suitable for highly connected networks like ours.
6. **Compute Weighted LeaderRank:** The prestige of each learner in the group was computed using the in-degree-weighted LeaderRank value, which adjusts the LeaderRank score by considering the indegree centrality, giving more weight to learners who receive more replies.
7. **Classify Learners:** Learners were classified into two categories: high-prestige and low-prestige. The top 50% of learners, based on their weighted LeaderRank scores, were classified as high-prestige learners, while the bottom 50% were classified as low-prestige learners.
8. **Repeat for All Groups:** Steps 4-7 were repeated four times for each group until the learner prestige of all groups was calculated.

In this study, 21 people were divided into 5 groups. The top 50% of the group were classified as high-prestige learners, while the remaining 50% were categorized as low-prestige learners. Each group contained 2 high-prestige learners. Four groups had 2 low-prestige learners, while one group had 3 low-prestige learners. In total, there were 10 high-prestige learners and 11 low-prestige learners.

[2] https://gephi.org/

[3] https://www.python.org/

4 Examining the regulatory behaviors of different prestige learners

To examine the regulatory behaviors of different prestige learners, we applied the ENA to explore the regulated learning patterns of different prestige learners and detail the three stages of PBL.

4.1 Comparison across regulatory types

The overall results are presented in Table 4. High-prestige learners have more regulatory behaviors than low-prestige learners. Mann-Whitney U test was used to evaluate the distribution of regulatory types. The results indicate a significant difference in SSR ($U = 24.0$, $Z = -2.183$, $p = 0.029$). This suggests that high-prestige learners have more SSR in the PBL process. They actively participate in goal formulation, goal achievement monitoring, and discussing and weighing the opinions provided in the group during the work.

The transcribed example from the group 3 is shown in Table 5. Learners are discussing the design of the database's relational model. Learner J is a low-prestige learner. Learner X and learner Q are high-prestige learners. During the conversation, learner J raises his concerns, which are addressed by learner X and learner Q. Two learners have a more in-depth discussion, but learner J is still confused and does not join the topic-related discussion because the question he does not understand has not yet been resolved.

4.2 Comparison across regulatory processes

In terms of the regulatory process, the most common behavior for both high-prestige and low-prestige learners is monitoring. The results of the Mann-Whitney U tests are displayed in Table 4, showing significant differences in monitoring behaviors ($U = 26.5$, $Z = -2.008$, $P = 0.043$). While completing the assignment, high-prestige learners actively perceive and monitor awareness of many components of cognitive, belief, emotional, and motivational states. They constantly observe and pay attention to task changes and team completion progress, and they contribute more to the team's task completion.

The transcribed example (Table 6) is from group 1. This example shows how Group 1 members were engaged in monitoring the necessity and implications of having a "teacher leader" entity within their work. Ja is a high-prestige learner. L and D are low-prestige learners. Ja initiates the discussion with the question, "Do we need this entity 'teacher leader'?" Ja reflects on the current team structure and guides the team members toward a deeper discussion and consideration of their needs. Following this, group 1 members began to discuss this question. After responses from L and D, Ja adds, "Yes, teacher leaders also need to lead teachers." By responding to other members' points, she not only acknowledges their input but also expands the discussion, enhancing its depth. She continues with, "Two entities now." Ja demonstrates her ability to monitor the discussion's progress, ensuring that everyone understands and agrees with the current direction.

Table 4 Differences in regulation between high- and low-prestige learners

	High prestige		Low prestige		U	Z	P
	M	SD	M	SD			
Self-regulation (SR)	26.60	24.910	16.45	10.280	46.5	-0.601	0.557
Co-regulation (CoR)	52.80	63.224	22.27	19.815	39.0	-1.129	0.282
Socially shared regulation (SSR)	171.90	134.588	76.73	35.080	24.0	-2.183	0.029*
Planning (P)	65.30	46.987	31.73	13.624	29.0	-1.833	0.072
Monitoring (M)	116.90	109.168	44.09	23.428	26.5	-2.008	0.043*
Regulating (R)	40.60	44.970	22.36	15.390	49.0	-0.423	0.705
Evaluating (E)	28.50	24.369	17.27	13.748	43.0	3.172	0.426
Task understanding (TU)	30.80	25.651	9.91	7.327	15.0	-2.829	0.004*
Content monitoring (CM)	103.00	96.692	49.36	30.490	41.0	-0.986	0.349
Process monitoring (PM)	60.10	57.514	25.27	11.620	29.0	-1.831	0.072
Positive emotion (PE)	13.70	14.507	7.82	8.507	40.0	-1.060	0.314
Negative emotion (NE)	12.90	14.426	7.64	4.567	50.0	-0.353	0.756
Joking (J)	5.40	5.502	7.18	11.754	53.5	-0.108	0.918
Organizing (O)	25.40	22.172	8.27	4.149	20.5	0.015	0.013*

Note:*P <0.05. There are 10 high-prestige learners and 11 low-prestige learners

Table 5 Transcribed example of group 3 regulation type

Name	Text
...	...
J	Is the sale considered an entity? The entity I understand is the product number.
X	A product number is an attribute.
Q	Yes, what follows (with entity) are attributes.
Q	How about combining buying and selling?
X	That's good.
Q	Uh-huh, what do other people think?
J	I don't quite understand the entity of sale, is sale a noun here?
...	...

We conducted an ENA to examine the regulatory processes of learners and determine whether there were differences in these processes among learners with different levels of prestige. We specifically considered the cyclical, temporal, and interdependent components of these processes. The first two dimensions of the ENA network model of the regulation process are depicted in Fig. 2, accounting for more than 70% of the variance. The MR1 axis accounts for 48.4% of the variance in the ENA, whereas the SVD2 axis (singular value decomposition, SVD) accounts for 28.7% of the variance of the data. The blue dots in Fig. 2 indicate each high-prestige student's ENA centroids. The red dots in the diagram depict the centroids of each low-prestige student, which are denoted with ENA. The squares reflect the mean positions, while the boxes represent the 95% confidence intervals. The right part of Fig. 2 displays the mean networks for high-prestige learners (blue) and low-prestige learners (red). Additionally, the network is weighted. The lighter, thinner lines represent connections the student made less frequently (weaker connections), whereas the darker, thicker lines show connections the student made more frequently (stronger connections).

Table 6 Transcribed example of group 1 regulation process

Name	Text
...	...
Ja	Do we need this entity 'teacher leader'? (Monitoring)
L	I think we can have it. (Monitoring)
L	That means separating leaders and regular employees. (Monitoring)
D	I were just thinking about this too. (Monitoring)
Ja	Yes, teacher leaders also need to lead teachers. (Monitoring)
Ja	Teacher leader and teacher hahaha. (Monitoring)
Ja	Two entities now. (Monitoring)
L	Hahaha we can have it. (Monitoring)
...	...

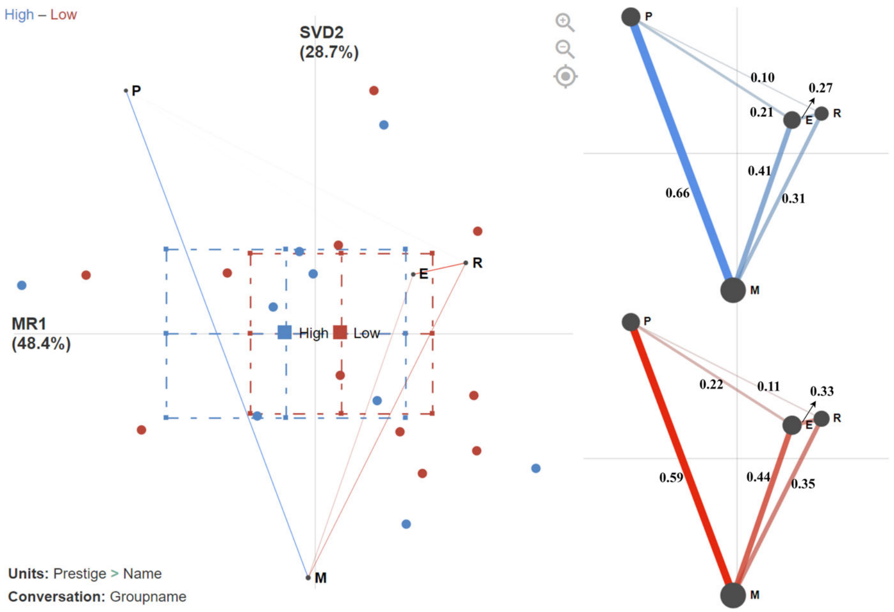

Fig. 2 ENA means, projected points, and mean networks of the regulatory process for students in high prestige (blue) and low prestige (red)

A Mann-Whitney U test is used to compare the distribution of projected points in the ENA space for each of the students. On the MR1 axis ($U = 68.00$, $p = 0.39 > 0.05$, $r = 0.24$) and the SVD2 axis ($U = 58.00$, $p = 0.86 > 0.05$, $r = -0.05$), the results indicate no significant differences.

To better understand the differences in regulatory processes low-prestige and high-prestige learners, we computed the mean networks of their regulation processes in three stages. Figure 3 (a) and (d) depict the ENA network in the regulatory processes of low-prestige and high-prestige learners, in the initial stage. High-prestige learners are found to have stronger connections on P-M, M-E, and P-E. On the other hand, low-prestige learners had stronger connections in R-E. High-prestige learners, who exhibit characteristics of leader-type learners, concentrate on understanding and planning the group task during the intra-group discussion stage, as well as monitoring its completion and evaluating it. They focus on the macro level of tasks, ensuring comprehensive oversight and strategic planning. Conversely, low-prestige learners have a stronger collinear relationship with planning regulation due to their initial lack of task understanding, necessitating revisions. Although low-prestige learners exhibit many evaluating behaviors, these evaluations are not about content, but about others' performance. For example, “Q, you're awesome!", “S, you're so good!", “A, you are my God!!!", “Good job!", “You're great.", etc.

Subfigures (b), (c), (e), and (f) in Fig. 3 depict ENA in the regulatory processes of high- and low-prestige learners in the inter-group assessment and intra-group refinement stages. The students' ENA network structures are very similar. Both high- and low-prestige learners depend heavily on monitoring. During the inter-group

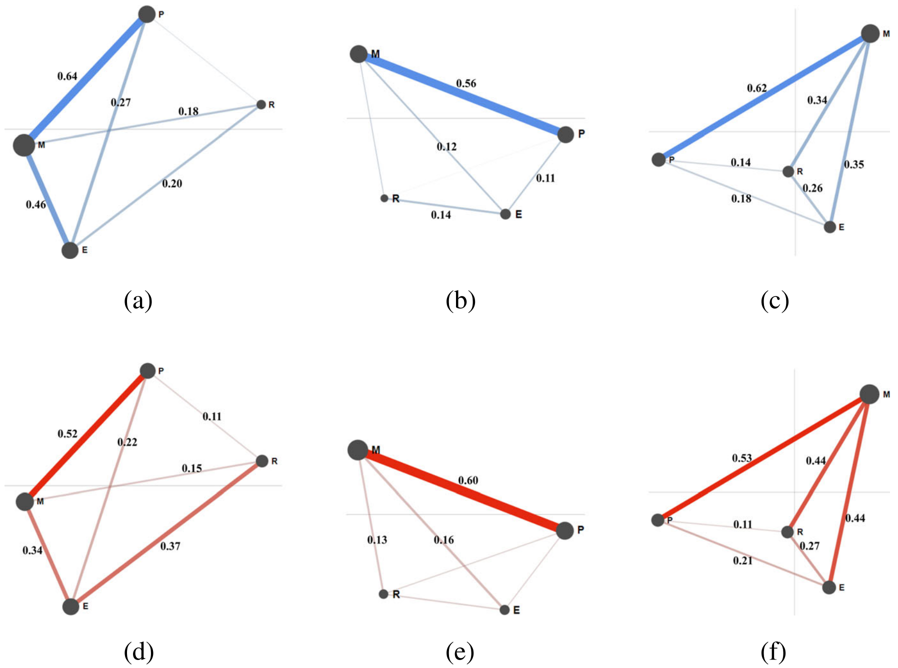

Fig. 3 Mean ENA network for high-prestige learners (blue) and low-prestige learners (red) in the learners' regulatory processes

assessment stage, high-prestige learners typically talk about task planning and monitor task processes. During the intra-group refinement stage, high-prestige learners often examine and assess relevant material and database system design works. High-prestige learners create a steady, closed loop of regulated learning behavior and actively support the development of PBL within the group.

4.3 Comparison across regulatory focuses

In Table 4, concentrating on the regulation focus, high-prestige and low-prestige learners vary significantly on TU (U = 15.0, Z = -2.829, p = 0.004) and O (U = 20.5, Z = 0.015, p = 0.013). High-prestige learners pay more attention to task comprehension and organizational aspects of the regulatory process than low-prestige learners. While performing the assignment, high-prestige learners are engaged in comprehending the task arrangement and requirements. They gather all of the group members to discuss and assign work together.

The transcribed example (Table 7) is from group 1 about discussing task assignments and execution. G and Ja are high-prestige learners, and L and D are low-prestige learners. G first discusses task objectives by asking, "This task, do we still take responsibility for our parts as before or reassign them?" This question reflects G's effort to clarify how the team will handle task division, ensuring an understanding of the overall task objectives and process. Ja's responses, "This should be written in the Shimo doc-

Table 7 Transcribed example of group 1 regulation focus

Name	Text
...	...
G	@Ja This task, do we still take responsibility for our own parts as before or reassign them? (Task understanding)
G	A total of 16 tables. (Task understanding)
Ja	This should be written in the Shimo document, right? (Task understanding)
Ja	We are responsible for our parts. (Task understanding)
L	OK, of course. (Task understanding)
G	@Ja OK, our tables also need to be placed in the Shimo document, I will put them in later. (Organizing)
L	Is this the only task this week? Just add five statements to each table. (Task understanding)
G	OK, if we encounter properties of data that are difficult to define during the process of doing this task, we can discuss them in the group to see whether to delete or modify them. (Organizing)
D	OK. (Task understanding)
G	@L It's about adding 5 pieces of data to each column using SQL statements. (Task understanding)
Ja	OK, that's doable. (Task understanding)
G	You are right. (Task understanding)
G	There are some similar attributes, such as foreign keys, which we need to discuss in the group to unify their usage. (Task understanding)
G	Do we need to write the foreign keys separately? (Task understanding)
D	What does it mean to not write separately? (Task understanding)
G	Foreign keys are primary keys in other tables, if the primary key in that table has already been added, then the foreign key in this table doesn't need to add data, right? (Task understanding)
...	...

ument, right?" and "We are responsible for our parts," indicate that Ja ensures all requirements and tasks are documented properly. These responses show Ja's understanding of the task's division and objectives, confirming that Ja comprehends the expectations and responsibilities of each team member. G explained in detail to D the task of adding data to each column using SQL statements. G also suggested discussing how to deal with data attributes that are difficult to define, indicating that G has a deep understanding of the task requirements. However, L mainly asks questions to confirm task requirements but lacks proactive suggestions or solutions. For instance, L asks if there is only one task this week but does not provide any specific suggestions on how to complete the task. L also provides limited information during task discussions and does not elaborate on the task specifics and technical details, unlike G, who provides detailed explanations (e.g., using SQL statements). As for D's participation in the discussion is minimal, mainly consisting of simple confirmations like "OK." Unlike G and Ja, D does not engage actively in task allocation and detailed discussions. When D asks about the meaning of "not write separately" regarding foreign keys, D does not propose any solutions, relying on others to provide answers.

Figure 4 presents the first two dimensions of the ENA network model of the regulatory focus, which accounts for more than 42.6% of the variation. To compare learners' distributions in the ENA space, we employed the Mann-Whitney U test. The outcomes are provided in Table 8. There is a significant difference between low-prestige learners (Mdn = 0.61, N = 11, U = 94.00, p = 0.00 <0.001, r = -0.71) and high-prestige learners (Mdn = -0.63, N = 10) along the MR1 axis. High-prestige learners (Mdn = -0.06, N = 10) and low-prestige learners (Mdn = -0.42, U = 47.00, p = 0.60 >0.001, r = 0.15) do not significant along the SVD2 axis. The line indicates a collinear relationship. The collinear link increases with line thickness. High-prestige learners outperform low-prestige learners in TU-PM and TU-CM. Low-prestige learners outperform high-prestige learners on CM-NE and CM-J. In the task and organizational behaviors, high-prestige learners are more concerned with TU, PM, and O. While low-prestige learners are also fully engaged in content monitoring, they are more emotionally immersed in the process. Emotions are more prevalent in low-prestige learners' CM and PM.

The Mann-Whitney U test results are exhibited in Table 9. During the PBL three-stage, along with the MR1 axis, the ENA of high-prestige and low-prestige learners reveals significant differences. The mean ENA network of the regulatory focus between high-prestige and low-prestige learners during the intra-group discussion stage is displayed in Figs. 5 (a) and (d). On CM-J and PM-J, low-prestige learners outperform high-prestige learners. In contrast, high-prestige learners have stronger collinearity for TU-PM, TU-PE, TU-J, and CM-PM than low-prestige learners. It suggests that the

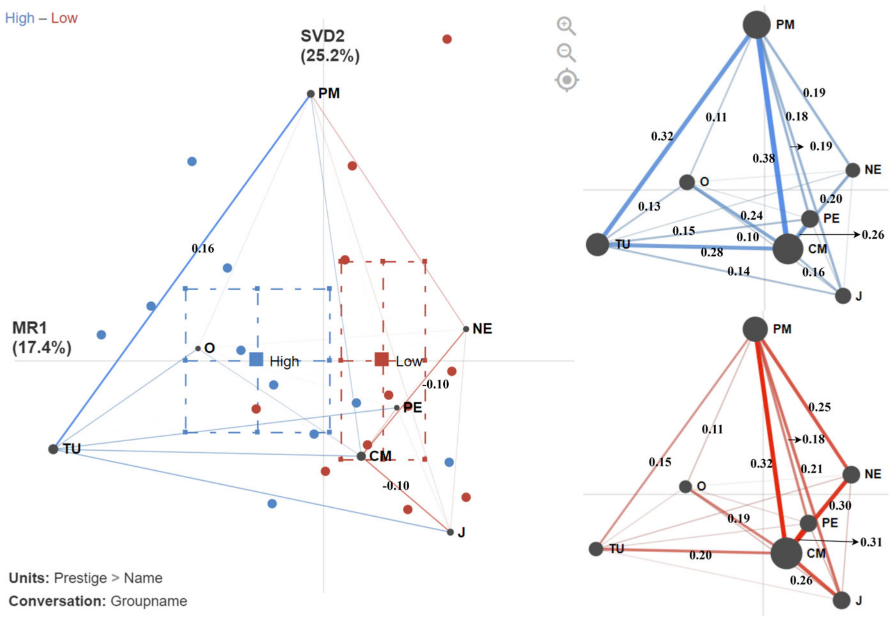

Fig. 4 ENA networks of the regulatory focus for the high-prestige learners (blue) and the low-prestige learners (red)

Table 8 Mann-Whitney U test results of regulatory focus

	N	MR1 axis				SVD axis			
		Mean	U	R	P	Mean	U	R	P
High-prestige learner	10	-0.63	94.00	-0.71	0.00***	-0.06	47.00	0.15	0.60
Low-prestige learner	11	0.61				-0.42			

Note:***P <0.001

high-prestige learners discussed the content most. If the task is not well understood, it will pose a great challenge to task understanding in the later stages. Subfigures (b) and (e) in Fig. 5 illustrate how low-prestige learners do better than high-prestige learners on CM-O, CM-NE, and NE-J during the intergroup assessment stage. Subfigures (c) and (f) in Fig. 5 show that high-prestige learners showed more collinearity in TU-CM, TU-PM, and TU-O during the intra-group refinement refining stage. Low-prestige learners had stronger relationships in the areas of CM-NE and PM-NE. This suggests that low-prestige learners concentrate on the regulation of emotions, whereas high-prestige learners focus on tasks and organization.

5 Influence of regulatory behavior on learners' prestige

Grey relation and regression analyses are performed to investigate the relationship between regulatory behavior and learners' prestige since it is not feasible to apply Spearman correlation analysis methods because of the small sample size. Considering this research's purpose and data characteristics, grey relational analysis is employed for correlation analysis. Grey relational analysis computes the similarity or dissimilarity in the developmental patterns of a feature sequence and a reference sequence to determine the degree of relationship between them. This approach can accurately identify from plenty of factors the primary ones that affect the aim (Azzeh et al., 2010).

Learner's prestige is measured by LeaderRank weighted by in-degree are taken as the characteristic variables of the system. Three influencing factors—SR, CoR, and SSR—are the correlation variables. A grey correlation degree analysis was carried out with the data of 21 learners. The correlation between regulatory type and prestige

Table 9 Mann-Whitney U test results of regulatory focus

		N	MR1 axis				SVD2 axis			
			Mean	U	R	P	Mean	U	R	P
P1	high prestige	10	0.89	107.00	-0.95	0.00**	-0.22	54.00	0.02	0.97
	low prestige	11	-0.89				-0.24			
P2	high prestige	10	0.17	85.00	-0.55	0.04*	0.43	58.00	-0.05	0.86
	low prestige	11	-0.27				0.35			
P3	high prestige	10	0.66	89.00	-0.62	0.02*	0.27	58.00	-0.05	0.86
	low prestige	11	-0.67				-0.13			

Note:*P <0.05, **P <0.01

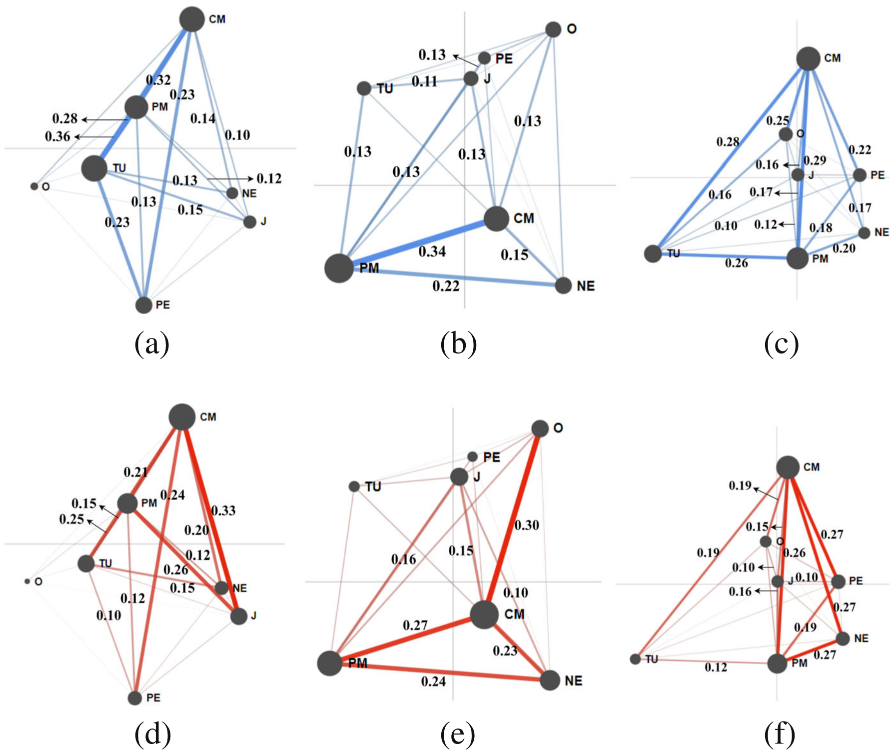

Fig. 5 Mean ENA network for high-prestige learners (blue) and low-prestige learners (red) in the students' regulatory focus

is shown in the first row of Fig. 6. From left to right are SR (GRG (Grey Relational Grade value) = 0.618), CoR (GRG = 0.641), and SSR (GRG = 0.780). SSR has the highest correlation with learners' prestige.

There is a strong correlation between socially shared regulation and learners' prestige (Göktepe Yıldız & Göktepe Körpeoğlu, 2023). The purpose of stepwise regression analysis is to uncover whether regulatory type predicted learner prestige. The second row in Table 10 shows the results on the link between SR, CoR, SSR, and learners' prestige. In this case, $R^2 = 0.878$, which means that SR and SSR jointly explained 87.8% of the variation in learners' prestige. According to the stepwise regression strategy, SSR ($\beta = 0.509$, t = 4.100, p = 0.001 <0.01) and SR ($\beta = 0.493$, t = 3.971, p = 0.001 <0.01) are included in the regression model. The research results show that SSR and SR can positively predict learners' prestige.

Figure 6 displays the regulatory process and prestige association in the second row. P (GRG = 0.658), M (GRG = 0.694), R (GRG = 0.628), and E (GRG = 0.616) are arranged from left to right. M and learner prestige are most correlated. The findings indicate that monitoring is the primary factor influencing learners' prestige during the regulatory process. Planning, monitoring, controlling, and assessing are used as independent variables, while learners' prestige is used as the dependent variable in

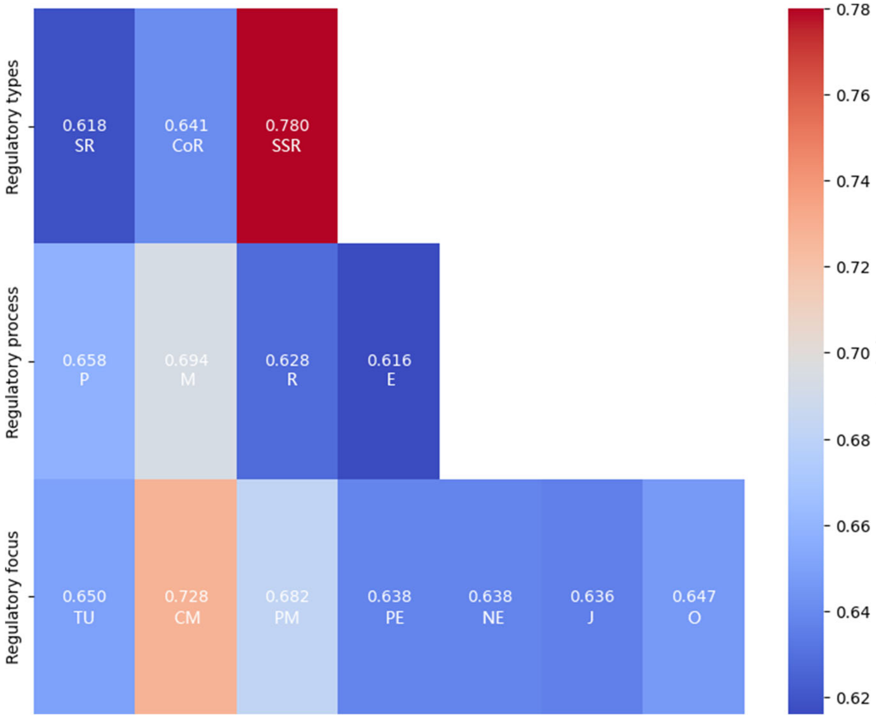

Fig. 6 Correlation between regulatory behavior and learner prestige

a stepwise regression analysis. The analysis findings are displayed in third row of Table 10. $R^2 = 0.817$, which means that monitoring and evaluating together explained 81.7% of the variation in learners' prestige. Monitoring ($\beta = 0.519$, $t = 3.085$, $p = 0.006 < 0.01$) and Evaluating ($\beta = 0.433$, $t = 2.571$, $p = 0.019 < 0.05$) are included in the regression model. This means that monitoring and evaluating behaviors can positively predict learners' prestige. Miller and Hadwin (2015) noted that monitoring is a key

Table 10 Stepwise regression analysis result (dependent variable = prestige)

Model	Indicators	β	t	R^2	ΔR^2
Regulatory type	Socially shared regulation (SSR)	0.509	4.100**	0.878	0.865
	Self-regulation (SR)	0.493	3.971**		
Regulatory process	Monitoring (M)	0.519	3.085**	0.817	0.797
	Evaluating (E)	0.433	2.571*		
Regulatory focus	Content monitoring (CM)	0.743	7.009**	0.869	0.855
	Process monitoring (PM)	0.275	2.593*		

Note:*P <0.05, **P <0.01. 1 represents the regression result of regulatory type and learner reputation. 2 represents the regression results of the regulatory process and learner reputation. 3 represents the regression results between regulatory focus and learner reputation part of the regulatory process and is triggered when regulation learning encounters new challenges or adaptations fail. By monitoring the learning task, the group identifies what has not yet been realized (Hadwin et al., 2017). Students identify problems in time and take appropriate measures to solve them. Evaluation means comparing one's or the group's performance as per the goals and uncovering the shortcomings. By summarizing and evaluating the process of task implementation, problems, and deficiencies can be identified and can provide valuable experience for the next task.

Figure 6 illustrates the association between regulatory emphasis and prestige. The variables are ordered as follows in decreasing order of their value: CM (GRG = 0.728), PM (GRG = 0.682), TU (GRG = 0.650), O (GRG = 0.647), PE (GRG = 0.638), NE (GRG = 0.638), and J (GRG = 0.636). The strongest relationship exists between CM and learner prestige. The regulatory focus findings are displayed in Table 10. $R^2 = 0.869$, which means that CM and PM together explain 86.9% of the variation in learners' prestige. CM ($\beta = 0.743$,t = 7.009, p = 0.000 <0.01) and PM ($\beta = 0.275$, t = 2.593, p = 0.018 <0.05) are included in the regression model. It implies that CM and PM can positively predict learners' prestige. This implies that by actively engaging in the learning process and keeping track of its advancement, students may elevate their prestige during PBL. CM is a regulation that examines, refines, revises, and improves team members' task responses (Järvelä et al., 2013; Lee et al., 2015). In addition to being a well-known indicator of superior regulation, content monitors are crucial for successful collaboration and efficient education (Volet et al., 2009). Since learners maintain track of their database knowledge and produce a comprehensive view of database development, the group's knowledge content may be shared. During this stage, learners demonstrate their leadership by reviewing the task's content and combining ideas to create changes to the work. PM refers to the process by which teams calculate how much time is left to complete the task by comparing the current state of ongoing collaborative projects to set goals or schedules. Learners can complete the homework on time if they utilize PM (Rogat & Linnenbrink-Garcia, 2011).

6 Discussion and implications

This study has several implications for teachers and instructors for the design and implementation of PBL. First, this study highlights the value of different prestige learners' social aspects of regulation in PBL. Socially shared regulation is the process by which learners regulate collective cognition, behavior, motivation, and emotions in a group. High-prestige learners are responsible for assigning, coordinating, and supervising the progress and quality of tasks within the group. Socially shared regulation is the process by which learners regulate collective cognition, behavior, motivation, and emotions in a group. Socially shared regulation requires group members to participate in project-based activities and learners to complete tasks with others. This is consistent with the findings of Santos et al. (2018) that high-prestige learners tend to be more collaborative than low-prestige learners. This study finds that socially shared regulation and self-regulation have a significant positive impact on the learner's prestige. Self-regulation refers to the process by which learners can monitor, check, evaluate, regulate, and improve their learning process according to the learning goals they set

(Schunk & Zimmerman, 2012; Winne et al., 2013; Winters & Alexander, 2011). Learners with good self-regulation learning ability can ensure the completion of their own learning goals. A high level of social regulation ensures the team's task completion quality (Grau & Whitebread, 2012; Ucan & Webb, 2015). Therefore, learners can be taught how to perform socially shared regulation and self-regulated learning at the early stages of learning. Socially shared regulation scaffolding can also be arranged and designed to enhance learners' prestige and learner leadership skills.

Second, high-prestige learners actively initiated and implemented monitoring strategies during the task. Monitoring and evaluating have a positive impact on learners' prestige. Monitoring behavior is a core part of the regulation process (Zhang et al., 2021; Su et al., 2018). Miller and Hadwin (2015) pointed out that monitoring is a key link in the regulatory process. When regulated learning encounters new challenges or adaptive regulation fails, monitoring is triggered. By monitoring learning tasks, the team can identify unmet goals, quickly discover problems, and take measures to solve them (Hadwin et al., 2017). Evaluation involves comparing performance against a standard to identify deficiencies. By summarizing and assessing the task implementation process, problems can be identified, offering valuable insights for future tasks.

Third, high-prestige learners outperformed low-prestige learners on Task Understanding and Organization. This is consistent with existing research conclusions. Morgeson et al. (2010) noted that high-prestige learners play key roles in the early stages of collaborative task completion, including forming teams, determining topics, setting goals, planning tasks, and explaining assignments. Neely Jr et al. (2020) found that the characteristics and experience of leaders will affect the team's choices, which in turn will produce the team's behavioral performance. Gray correlation analysis indicates that the relationship between content monitoring and learner prestige is the most significant. Additionally, regression analysis reveals that both content monitoring and process monitoring significantly enhance learner prestige. Content monitoring is a regulatory measure to check, refine, revise, and improve the task responses of team members (Lee et al., 2015; Rogat & Linnenbrink-Garcia, 2011). Content monitoring is not only a recognized indicator of high-quality regulation but also plays a crucial role in successful collaboration and effective learning (Volet et al., 2009). Students' monitoring of database system knowledge can gather the knowledge content of the group and form a complete database system development opinion. In this process, checking the task content and revising the task based on the opinions can reflect the learner's leadership. Process monitoring is when each group checks the progress of the current collaborative activities against the established goals or plans, as well as the remaining time to complete the task, and urges themselves or all team members to complete the task on time (Rogat & Linnenbrink-Garcia, 2011).

Finally, social-emotional regulation plays a key role in PBL. Emotional regulation contributes to a favorable collaborative learning climate that leads to the sharing of ideas, the presentation of opinions, and high levels of cognitive interaction toward problem-solving. If there is a lack of effective emotional regulation, disruptive participation and monitoring can interfere with optimal cognitive functioning. High-prestige learners will always invest more effort in the task even in different stages of PBL (Kwon et al., 2014). High-prestige learners will always invest more effort in the task even in different stages of PBL. This behavior can be attributed to their need to express emotions and seek social connection within the group. Emojis serve as a non-verbal communication tool that can help low-prestige learners convey their feelings, facilitating their discussion engagement. Low-prestige learners will send more emojis in the intra-group discussion stage (Cherbonnier & Michinov, 2021; Li et al., 2024; Kelly & Watts, 2015). With the deepening of the task and the increasing difficulty of the task, low-prestige learners presented more messages with negative emotions. Social interactions occur concurrently with emotional interactions and are intertwined with cognitive and task-related interactions. Negative emotions in low-prestige learners are triggered by the learning content (Isohätälä et al., 2020; Mänty et al., 2020; Tatiana et al., 2022).

7 Conclusion and future work

This paper analyzed students' discourse data in the course *Database and its Principles*. The students were classified into high-prestige learners and low-prestige learners by their LeaderRank values and indegree centrality. Statistical analysis, content analysis, and ENA were used to explore the influence of regulatory behavior on prestige. The study reveals that high- and low-prestige learners have different regulated learning patterns. These differences are reflected in the "socially shared regulation," "monitoring," "task understanding," and "organizing." There are also significant differences in regulatory focus between high- and low-prestige learners at different stages of PBL. During the intra-group discussion stage, high-prestige learners prioritized the task dimension. Conversely, in the inter-group assessment stage and the intra-group refinement stage, high-prestige learners demonstrated more positive emotions, whereas low-prestige learners showed higher levels of negative emotional engagement. Gray correlation analysis found correlations between content monitoring, social adaptation, and learner reputation. Stepwise regression analysis results show that socially shared regulation, self-regulation, monitoring and evaluation, content monitoring, and process monitoring all significantly positively impact learner prestige.

This study proposes that students can gain more prestige in social discourse by scaffolding for self-regulation or socially shared learning scaffolding, as well as by designing relevant regulation learning scripts. Teachers can use a variety of strategies to support students' responsibility for their learning and improve their prestige. Through these strategies, students will become more aware of how to monitor both their own and their group's learning, as well as how to reflect on it to enhance their prestige. The discourses in the PBL process should also be analyzed and displayed using deep learning and other artificial intelligence technologies, which enable accelerated and dynamic learner monitoring. This will enable students to receive comments promptly so they can understand group work better.

While the findings of this study revealed the relationship between learners' prestige and regulated learning, there are some limitations to consider. First, this study is based on data collected from only one course. Future research needs to examine whether other course contexts impact learner prestige and regulation, and whether personal characteristics (such as cultural background) affect learner reputation and regulation.

In future studies, large language models (LLMs) can be used to automatically capture students' response patterns in the CSCL group, allowing for real-time monitoring of changes in learner reputation. Ethical issues should also be addressed to ensure the privacy and confidentiality of participants, especially when dealing with sensitive data related to learner reputation and behavior. Based on neuroscience insights, Kong and Yang (2024) guide students to use generative AI tools to enhance attentiveness, stimulate active learning, receive immediate feedback, and encourage self-reflection during self-regulation learning. Future research could explore how to use generative AI to assist social shared regulation in the PBL groups.

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Data Availability Statement The datasets and code generated during the current study will be available in the GitHub repository.

Code Availability The code will be released to GitHub once the paper being published.

Declarations

Informed consent The authors did not receive support from any organization for the submitted work.

References

Azzeh, M., Neagu, D., & Cowling, P. I. (2010). Fuzzy grey relational analysis for software effort estimation. *Empirical Software Engineering, 15*(1), 60–90. https://doi.org/10.1007/s10664-009-9113-0

Balkundi, P., Kilduff, M. (2006). The ties that lead: A social network approach to leadership.

Bandura, A. (1997). Self-eficacy: The exercise of control. *Freeman & Co Student Success, 333*, 48461.

Boekaerts, M. (1996). Self-regulated learning at the junction of cognition and motivation. *European psychologist, 1*(2), 100–112. https://doi.org/10.1027/1016-9040.1.2.100

Borgatti, S. P., & Brass, D.J. (2019). Centrality: Concepts and measures. *Social networks at work* (pp. 9–22).

Borgatti, S. P., Mehra, A., Brass, D. J., et al. (2009). Network analysis in the social sciences. *Science, 323*(5916), 892–895.

Cao, C., Chen, B., Yang, S., et al. (2022). Exploring the impact of individual and social antecedents on teachers' teaching innovation: Perspective of goal-oriented behavior and social identity. *Frontiers in Psychology, 13*, 924052.

Carletta, J. (1996). Assessing agreement on classification tasks: The kappa statistic. *Computational Linguistics, 22*(2), 249–254.

Chen, C. H., & Yang, Y. C. (2019). Revisiting the effects of project-based learning on students' academic achievement: A meta-analysis investigating moderators. *Educational Research Review, 26*, 71–81. https://doi.org/10.1016/j.edurev.2018.11.001

Chen, J., Kolmos, A., & Du, X. (2021). Forms of implementation and challenges of pbl in engineering education: a review of literature. *European Journal of Engineering Education, 46*(1), 90–115. https://doi.org/10.1080/03043797.2020.1718615

Cheng, C. C., & Yang, Y. T. C. (2023). Impact of smart classrooms combined with student-centered pedagogies on rural students' learning outcomes: Pedagogy and duration as moderator variables. *Computers & Education, 207*, 104911. https://doi.org/10.1016/j.compedu.2023.104911
Cherbonnier, A., & Michinov, N. (2021). The recognition of emotions beyond facial expressions: Comparing emoticons specifically designed to convey basic emotions with other modes of expression. *Computers in Human Behavior, 118*, 106689. https://doi.org/10.1016/j.chb.2021.106689
De Oliveira Biazus, M., & Mahtari, S. (2022). The impact of project-based learning (pjbl) model on secondary students' creative thinking skills. *International Journal of Essential Competencies in Education, 1*(1), 38–48. https://doi.org/10.36312/ijece.v1i1.752
Dignath, C., & Büttner, G. (2008). Components of fostering self-regulated learning among students. a meta-analysis on intervention studies at primary and secondary school level. *Metacognition and Learning, 3*, 231–264. https://doi.org/10.1007/s11409-008-9029-x
Dillenbourg, P., Järvelä, S., & Fischer, F. (2009). The evolution of research on computer-supported collaborative learning: From design to orchestration. Springer.
Dowell, N., Skrypnyk, O., Joksimovic, S., et al. (2015). Modeling learners' social centrality and performance through language and discourse. In Proceedings of the 8th international conference on educational data mining (pp. 250-257). International Educational Data Mining Society.
Duan, J., Xie, K., & Zhao, Q. (2024). A personal social knowledge network (PSKN) facilitates learners' wayfinding and its differences in behavior patterns between high and low performers in connectivist learning. *Int J Educ Technol High Educ, 21*, 22. https://doi.org/10.1186/s41239-024-00454-5
Göktepe Yıldız, S., & Göktepe Körpeoğlu, S. (2023). Prediction of students' perceptions of problem solving skills with a neuro-fuzzy model and hierarchical regression method: A quantitative study. *Education and Information Technologies* (pp. 1–39). https://doi.org/10.1007/s10639-022-11446-1
Grau, V., & Whitebread, D. (2012). Self and social regulation of learning during collaborative activities in the classroom: The interplay of individual and group cognition. *Learning and Instruction, 22*(6), 401–412.
Greimel, N. S., Kanbach, D. K., & Chelaru, M. (2023). Virtual teams and transformational leadership: An integrative literature review and avenues for further research. *Journal of Innovation & Knowledge, 8*(2), 100351. https://doi.org/10.1016/j.jik.2023.100351
Hacker, D. J., Dunlosky, J., & Graesser, A. C. (Eds.) (1998). Metacognition in educational theory and practice. Lawrence Erlbaum Associates Publishers.
Hadwin, A., & Oshige, M. (2011). Self-regulation, coregulation, and socially shared regulation: Exploring perspectives of social in self-regulated learning theory. *Teachers College Record, 113*(2), 240–264. https://doi.org/10.1177/016146811111300204
Hadwin, A., Järvelä, S., & Miller, M. (2017). Self-regulation, co-regulation, and shared regulation in collaborative learning environments. In: *Handbook of self-regulation of learning and performance* (pp. 83–106). Routledge. https://doi.org/10.4324/9781315697048-6
Hamad, S., Tairab, H., Wardat, Y., et al. (2022). Understanding science teachers' implementations of integrated stem: Teacher perceptions and practice. *Sustainability, 14*(6), 3594. https://doi.org/10.1186/s40594-018-0101-z
Han, Z. M., Huang, C. Q., Yu, J. H., & Tsai, C. C. (2021). Identifying patterns of epistemic emotions with respect to interactions in massive online open courses using deep learning and social network analysis. *Computers in Human Behavior, 122*, 106843. https://doi.org/10.1016/j.chb.2021.106843
Isohätälä, J., Näykki, P., Järvelä, S. (2020). Cognitive and socio-emotional interaction in collaborative learning: Exploring fluctuations in students' participation. *Scandinavian Journal of Educational Research, 64*(6), 831–851. https://www.tandfonline.com/doi/full/10.1080/00313831.2019.1623310
Järvelä, S., & Hadwin, A. F. (2013). New frontiers: Regulating learning in cscl. *Educational Psychologist, 48*(1), 25–39. https://doi.org/10.1080/00461520.2012.748006
Järvelä, S., & Järvenoja, H. (2011). Socially constructed self-regulated learning and motivation regulation in collaborative learning groups. *Teachers College Record, 113*(2), 350–374. https://doi.org/10.1177/016146811111300205
Järvelä, S., Järvenoja, H., Malmberg, J., et al. (2013). Exploring socially shared regulation in the context of collaboration. *Journal of Cognitive Education and Psychology, 12*(3), 267–286. https://doi.org/10.1891/1945-8959.12.3.267
Järvelä, S., Järvenoja, H., Malmberg, J., et al. (2016a). How do types of interaction and phases of self-regulated learning set a stage for collaborative engagement? *Learning and Instruction, 43*, 39–51. https://doi.org/10.1016/j.learninstruc.2016.01.005

Järvelä, S., Kirschner, P. A., Hadwin, A., et al. (2016b). 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*, 263–280. https://doi.org/10.1007/s11412-016-9238-2

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*, 425–441. https://doi.org/10.1007/s11412-019-09313-2

Järvenoja, H., & Järvelä, S. (2009). Emotion control in collaborative learning situations: Do students regulate emotions evoked by social challenges. *British Journal of Educational Psychology, 79*(3), 463–481. https://doi.org/10.1348/000709909X402811

Jeong, H., & Hmelo-Silver, C. E. (2016). Seven affordances of computer-supported collaborative learning: How to support collaborative learning? how can technologies help? *Educational Psychologist, 51*(2), 247–265.

Karpudewan, M., Ponniah, J., & Md. Zain, A. N. (2016). Project-based learning: An approach to promote energy literacy among secondary school students. *The Asia-Pacific Education Researcher, 25*, 229–237. https://doi.org/10.1007/s40299-015-0256-z

Kelly, R., & Watts, L. (2015). *Characterising the inventive appropriation of emoji as relationally meaningful in mediated close personal relationships*. Paper presented at Experiences of Technology Appropriation: Unanticipated Users, Usage, Circumstances, and Design, Oslo, Norway.

Kleinberg, J. M. (1999). Authoritative sources in a hyperlinked environment. *Journal of the ACM (JACM), 46*(5), 604–632. https://doi.org/10.1145/324133.324140

Kong, S. C., & Yang, Y. (2024). A human-centred learning and teaching framework using generative artificial intelligence for self-regulated learning development through domain knowledge learning in k–12 settings. IEEE Transactions on Learning Technologies. IEEE Transactions on Learning Technologies. https://ieeexplore.ieee.org/document/10507034

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. https://doi.org/10.1016/j.compedu.2014.06.004

Lee, A., O'Donnell, A. M., & Rogat, T. K. (2015). Exploration of the cognitive regulatory sub-processes employed by groups characterized by socially shared and other-regulation in a cscl context. *Computers in Human Behavior, 52*, 617–627. https://doi.org/10.1016/j.chb.2014.11.072

Li, Q., & Sharma, P. (2023). The effects of learners' background and social network position on content-related MOOC interaction. *Educational Technology Research and Development, 71*(3), 973–990. https://doi.org/10.1007/s11423-023-10221-4

Li, Y., Ma, S., Zhang, Y., et al. (2013). An improved mix framework for opinion leader identification in online learning communities. *Knowledge-Based Systems, 43*, 43–51. https://doi.org/10.1016/j.knosys.2013.01.005

Li, Y., Zhang, D., Liu, X., & Guo, D. (2024). Processing facial emojis as social information: Evidence from visual working memory for facial emojis, simple shapes, human faces, and their relations to theory of mind. *Computers in Human Behavior, 153*, 108106. https://doi.org/10.1016/j.chb.2023.108106

Liang, H., Qi, C., Huang, R., et al. (2024). Mathematics teachers' interaction patterns and role changes in online research-practice partnerships: A social network analysis. *Computers & Education* (p. 105077).

Liao, H., Mariani, M. S., Medo, M., et al. (2017). Ranking in evolving complex networks. *Physics Reports, 689*, 1–54.

Liu, Z., Zhang, N., Peng, X., Liu, S., Yang, Z., Peng, J., Su, Z., & Chen, J. (2022). Exploring the Relationship Between Social Interaction, Cognitive Processing and Learning Achievements in a MOOC Discussion Forum. *Journal of Educational Computing Research, 60*(1), 132–169. https://doi.org/10.1177/07356331211027300

Lü, L., Zhang, Y. C., Yeung, C. H., et al. (2011). Leaders in social networks, the delicious case. *PloS one, 6*(6), e21202. https://doi.org/10.1371/journal.pone.0021202

Mänty, K., Järvenoja, H., & Törmänen, T. (2020). Socio-emotional interaction in collaborative learning: Combining individual emotional experiences and group-level emotion regulation. *International Journal of Educational Research, 102*, 101589. https://doi.org/10.1016/j.ijer.2020.101589

Marcos-García, J. A., Martínez-Monés, A., & Dimitriadis, Y. (2015). Despro: A method based on roles to provide collaboration analysis support adapted to the participants in cscl situations. *Computers & Education, 82*, 335–353. https://doi.org/10.1016/j.compedu.2014.10.027

Maros, M., Korenkova, M., Fila, M., et al. (2023). Project-based learning and its effectiveness: evidence from slovakia. *Interactive Learning Environments, 31*(7), 4147–4155. https://doi.org/10.1080/10494820.2021.1954036

Mehra, A., Dixon, A. L., Brass, D. J., et al. (2006). *The social network ties of group leaders: Implications for group performance and leader reputation, 17*(1), 64–79. https://doi.org/10.1287/orsc.1050.0158, https://pubsonline.informs.org/doi/10.1287/orsc.1050.0158

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. https://doi.org/10.1016/j.chb.2015.01.050

Miyake, N., & Kirschner, P. A. (2014). *The Social and Interactive Dimensions of Collaborative Learning*. Cambridge University Press.

Morgeson, F. P., DeRue, D. S., & Karam, E. P. (2010). Leadership in teams: A functional approach to understanding leadership structures and processes. *Journal of Management, 36*(1), 5–39. https://doi.org/10.1177/0149206309347376

Neely, B. H., Jr., Lovelace, J. B., Cowen, A. P., et al. (2020). Metacritiques of upper echelons theory: Verdicts and recommendations for future research. *Journal of Management, 46*(6), 1029–1062. https://doi.org/10.1177/0149206320908640

Oh, E. G., Huang, W. H. D., Hedayati Mehdiabadi, A., et al. (2018). Facilitating critical thinking in asynchronous online discussion: comparison between peer-and instructor-redirection. *Journal of Computing in Higher Education, 30*, 489–509. https://doi.org/10.1007/s12528-018-9180-6

Oliveira, J. M. N. d. (2023). Reflecting on 21 years of running full pbl programs. In: *Frontiers in Education, Frontiers*, (p. 1033764). https://doi.org/10.3389/feduc.2023.1033764

Ouyang, F., & Dai, X. (2022). Using a three-layered social-cognitive network analysis framework for understanding online collaborative discussions. *Australasian Journal of Educational Technology, 38*(1), 164–181. https://doi.org/10.14742/ajet.7166

Page, L. (1998). The pagerank citation ranking: Bringing order to the web. technical report. Stanford Digital Library Technologies Project, 1998.

Rienties, B., Køhler Simonsen, H., & Herodotou, C. (2020). Defining the Boundaries Between Artificial Intelligence in Education, Computer-Supported Collaborative Learning, Educational Data Mining, and Learning Analytics: A Need for Coherence. Frontiers in Education, 5. https://doi.org/10.3389/feduc.2020.00128

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. https://doi.org/10.1080/07370008.2011.607930

Rosé, C. (2017). A social spin on language analysis. *Nature, 545*, 166–167. https://doi.org/10.1038/545166a

Santos, F. P., Santos, F. C., & Pacheco, J. M. (2018). Social norm complexity and past reputations in the evolution of cooperation. *Nature, 555*(7695), 242–245.

Saqr, M., Elmoazen, R., Tedre, M., López-Pernas, S., & Hirsto, L. (2022). How well centrality measures capture student achievement in computer-supported collaborative learning? – A systematic review and meta-analysis. *Educational Research Review, 35*, 100437. https://doi.org/10.1016/j.edurev.2022.100437

Schoor, C., & Bannert, M. (2011). Motivation in a computer-supported collaborative learning scenario and its impact on learning activities and knowledge acquisition. *Learning and Instruction, 21*(4), 560–573.

Schunk, D. H., & Zimmerman, B. J. (2012). *Motivation and self-regulated learning: Theory, research, and applications*. Routledge.

Serrano-Cámara, L. M., Paredes-Velasco, M., Alcover, C. M., et al. (2014). An evaluation of students' motivation in computer-supported collaborative learning of programming concepts. *Computers in human behavior, 31*, 499–508.

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. https://doi.org/10.18608/jla.2016.33.3

Sparrowe, R. T., & Kraimer, M. L. (2024). Social networks and the performance of individuals and groups.

Stahl, C., Voss, A., Schmitz, F., et al. (2014). Behavioral components of impulsivity. *Journal of Experimental Psychology: General, 143*(2), 850.

Su, Y., Li, Y., Hu, H., et al. (2018). Exploring college english language learners' self and social regulation of learning during wiki-supported collaborative reading activities. *International journal of computer-supported collaborative learning, 13*, 35–60. https://doi.org/10.1007/s11412-018-9269-y

Tatiana, S., Hanna, J., Kristiina, M., et al. (2022). The changes in lower secondary school students' interest during collaborative learning. *Scandinavian Journal of Educational Research, 66*(7), 1127–1140.

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.

Volet, S., Summers, M., & Thurman, J. (2009). High-level co-regulation in collaborative learning: How does it emerge and how is it sustained? *Learning and Instruction, 19*(2), 128–143. https://doi.org/10.1016/j.learninstruc.2008.03.001

Wei, X., Chen, Y., Shen, J., et al. (2024). Fail or pass? investigating learning experiences and interactive roles in MOOC discussion board *217*, 105073. https://doi.org/10.1016/j.compedu.2024.105073, https://linkinghub.elsevier.com/retrieve/pii/S0360131524000873

Wen, Y. (2019). Computer-supported collaborative Chinese second language learning: Beyond brainstorming. Springer Nature.

Wen, Y., Looi, C. K., & Chen, W. (2011). Towards a model for rapid collaborative knowledge improvement in classroom language learning.

Winne, P. H. (2013). Self-regulated learning viewed from models of information processing. *Self-regulated learning and academic achievement* (pp. 145–178).

Winne, P. H., & Perry, N. E. (2000). Measuring self-regulated learning. In: *Handbook of self-regulation* (pp. 531–566). Elsevier. https://doi.org/10.1016/B978-012109890-2/50045-7

Winne, P. H., Hadwin, A. F., & Perry, N. E. (2013). Metacognition and computer-supported collaborative learning. In: *The international handbook of collaborative learning* (pp. 462–479). Routledge

Winters, F. I., & Alexander, P. A. (2011). Peer collaboration: The relation of regulatory behaviors to learning with hypermedia. *Instructional Science, 39*, 407–427.

Wu, B., & Wu, C. (2021). Research on the mechanism of knowledge diffusion in the MOOC learning forum using ERGMs. *Computers & Education, 173*, 104295. https://doi.org/10.1016/j.compedu.2021.104295

Zhang, L., & Ma, Y. (2023). A study of the impact of project-based learning on student learning effects: A meta-analysis study. *Frontiers in Psychology, 14*,. https://doi.org/10.3389/fpsyg.2023.1202728

Zhang, S., Chen, J., Wen, Y., et al. (2021). Capturing regulatory patterns in online collaborative learning: A network analytic approach. *International Journal of Computer-supported Collaborative Learning, 16*, 37–66. https://doi.org/10.1007/s11412-021-09339-5

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. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology, 81*(3), 329. https://doi.org/10.1037/0022-0663.81.3.329

Zimmerman, B. J. (2000). Chapter 2 - Attaining Self-Regulation: A Social Cognitive Perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), Handbook of Self-Regulation (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7

Zou, W., Hu, X., Pan, Z., et al. (2021). Exploring the relationship between social presence and learners' prestige in mooc discussion forums using automated content analysis and social network analysis. *Computers in Human Behavior, 115*, 106582. https://doi.org/10.1016/j.chb.2020.106582