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TOPICAL REVIEW

Data-Driven Support Infrastructure for Iterative Team-Based Learning

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ABSTRACT Iterative team-based learning (TBL) is a common educational strategy for collaborative learning that involves sequential phases of individual and group learning activities. The advent of digital learning platforms, with the accumulation of learning log data, presents an opportunity to leverage data-driven techniques to enhance TBL practices. However, applying data-driven approaches in iterative TBL scenarios has received limited exploration in existing literature. Through a review of initial studies in this domain, data-driven iterative TBL emerges as a promising area. To explore this topic, we introduce a novel framework, drawing from the GLOBE framework for group learning, aimed at integrating data-driven designs into iterative TBL settings. This framework is proposed to guide data and activity design within iterative TBL, comprising four phases of group learning activity workflow and three essential steps of data flow. Additionally, we present two authentic instances supported by empirical evidence, offering insights into how educators can implement data-driven designs across different phases of TBL. Within the data-driven environment, we also uncover potential impacts and challenges of data-driven iterative TBL, to identify avenues for future research that can further expand our understanding of the possibilities in this domain.

INDEX TERMS Team-based learning (TBL), collaborative learning, group formation, peer evaluation, rater reliability, data-driven support, computer-supported collaborative learning (CSCL), learning analytics (LA).

I. INTRODUCTION

Collaborative Learning is widely embraced in contemporary education due to its emphasis on the social-emotional aspects of learning [1] and the value placed on interpersonal skills in modern society [2]. One specific implementation of group learning is Team-Based Learning (TBL), an educational strategy comprising sequential phases of individual and group learning activities, as well as peer evaluation. This approach often spans multiple rounds and encompasses an entire semester, functioning as an iterative process [3].

A. ITERATIVE TEAM-BASED LEARNING

TBL was initially introduced in medical education [4] and revolves around flipped learning practice within small groups, departing from traditional lecture-driven instruction. As a typical form of flipped learning, learners utilize class time for in-depth discussions, problem-solving, and application of concepts initially acquired through individual learning assignments [5]. The process commences with individual learning based on provided materials, followed by group discussions and activities designed to foster critical thinking, problem-solving, and decision-making. The former steps can recur iteratively, enabling learners to reflect on their progress and enhance their skills through formative feedback in each iteration [3]. In this paper, we focus on this type of design as iterative TBL. Extensive studies have examined the dynamics of teamwork within this context, exploring various facets such as transition processes, action dynamics, and interpersonal relationships [6].

TBL can also adapt to hybrid learning contexts through computer-mediated support, known as computer-supported

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team-based learning (CS-TBL) [5]. As a sub-field of Computer-Supported Collaborative Learning (CSCL) [2], CS-TBL leverages communication tools such as online forums and hybrid meeting rooms, enabling asynchronous learning and overcoming the constraints of physical space and time. This flexibility is valuable during recent global pandemics, as it offers convenience and expanded opportunities for interaction in hybrid learning environments. Existing studies have shown that CS-TBL is effective in improving learner motivation, engagement, and overall learning outcomes.

B. DATA-DRIVEN SUPPORT FOR EDUCATION

In the meantime, the promotion of educational ICT environments and the installation of computer-based learning systems have generated a substantial amount of educational data pertaining to student learning behavior [7]. This data holds great promise for learning analytics (LA), which involves measuring, collecting, analyzing, and reporting data about learners and their contexts with the aim of improving the learning environment [8], [9] and, in turn, influencing their learning behaviors and improving outcomes through appropriate remedial actions [10], [11], [12]. In various educational settings, including TBL, predictive analytics can be conducted using learning log data previously generated by students [9], [11].

Teacher concerns regarding using computers in teaching primarily revolve around time-saving, personalization, and assessment [13]. To orchestrate a successful TBL, teachers must carefully plan the lesson, facilitate collaboration, motivate students, ensure learning, and evaluate achievements. However, this process can be time-consuming. For example, teachers often spend considerable time aligning students based on different learning contexts [14]. In online environments like MOOCs (Massive Open Online Courses), the lack of information about students can make it challenging to create appropriate groups [15]. Furthermore, due to limited workload capacity, teachers struggle to provide personalized and accurate interventions and feedback to every student or group [16], [17], [18]. Therefore, addressing these concerns by incorporating data-driven design using learning logs and prediction models from LA holds significant promise. For example, automated group formation with data can save time, enabling personalization using various indicators. Additionally, a peer evaluation system can assist in assessing group work and collecting data for subsequent formation.

Many studies in collaborative learning field have primarily focused on utilizing learner attribute data to predict performance [19], aid decision-making for incident detection [20], and to provide formative feedback through data visualization [21], [22]. For instance, the significance of domain knowledge has been emphasized in problem-solving tasks that require high knowledge construction [23], [24]. As a result, learners' prior knowledge and skills is taken into consideration when assigning them to appropriate group members [25], [26], [27]. Additionally, personality traits from the Big Five models, particularly the aspect of externality that reflects collaborative tendencies, have been examined to enhance collaboration and improve learning outcomes [28]. Furthermore, group-level indicators, such as group size, cohesion and intimacy among members, have been investigated in various studies for its impact on group performance and production [27], [29], [30]. In addition to performance prediction, behavior models from sequence analysis and network analysis are widely used to examine group dynamics during the learning process [31], [32], [33], [34]. Moreover, researchers have attempted to provide group awareness information by focusing on key factors of learning activities, enabling timely scaffolding of learners during group learning. This computational artifact can mediate collaboration and unveil CSCL processes [35]. Examples include customized instructions based on equal contributions in collaborative wikis [21] and the visualization of group knowledge maps in collaborative search [36].

TABLE 1. Comparative table of main bibliographic references on TBL and data-driven studies.

References	Contributions	Limitations
[3]–[6]	TBL conceptualization and CS-TBL advancement.	Despite the facilitation of ICT in CS-TBL, **data-driven design is limited**.
[9]–[12]	Data-driven support and LA studies for educational practice.	Not specified in and CS-TBL field.
[19], [20], [23]–[30]	Group formation and performance prediction before group learning.	Concentrate on data usage within a **single TBL episode**, while overlook the potential for reusing data in long-term scenarios with **multiple (iterative) TBL activities**.
[31]–[34]	Group dynamics modeling during group learning.	
[21], [22], [35], [36]	Group awareness support for group learning.	

C. CONTRIBUTIONS AND INNOVATION OF THIS WORK

Table 1 summarizes the aforementioned studies on TBL and data-driven implementations. On the one hand, conventional TBL studies derive from classroom-based scenarios. Despite advancements in scaffolding services with computers for online environments, data-driven design is less addressed. On the other hand, LA studies utilize educational big data to enhance educational practice. They have focused on learner attribute data, depicting and scaffolding manifold aspects of group learning. However, their data usage is often confined to a single TBL episode, overlooking the potential for reusing data in long-term scenarios with multiple times of TBL activities.

Iterative TBL, which involves consecutive group works, is a typical context where the data cycle of reuse is crucial. By accumulating learning evidence from outside and within the group learning context, a more flexible framework can be developed to support iterative TBL designs in various learning contexts. Through a review of the aforementioned initial studies, data-driven iterative TBL emerges as a promising area to explore further.

Accordingly, to enhance iterative TBL processes with data support and address the limitations of existing data-driven studies, this topical review proposes a data-driven framework, which covers three steps of data-driven design in four phases of CSCL [37]. The proposed framework aims to integrate various data sources, including learning log behaviors such as e-book reading logs, to support all phases of group learning. By incorporating data accumulated from multiple rounds of TBL implementations, the framework levels a playground for data-driven services and predictive models that contribute to developing optimal group learning environments.

D. PAPER STRUCTURE

In the subsequent sections, we will commence by introducing the data-driven design framework, focusing on the activity workflow of team-based learning, which encompasses individual learning and group learning phases. Next, we will delve into the potential and issues of data-driven support in each phase, drawing on recent studies. Following this, we will outline our data-driven support design, comprising three key steps: data synthesis, data utilization, and data analysis. To provide concrete insights into the framework's application within authentic scenarios, we will furnish examples of two enabling tasks. These examples also elicit the promising prospects of data-driven design across various group learning scenarios. In the subsequent discussion section, we will debrief several pertinent issues that may arise when implementing data-driven support in authentic learning contexts as the results of the topical review. These include considerations related to evaluation design, ethics, and the challenges encountered in the implementation process. Finally, in the conclusion section, we will summarize the main contributions of this topical review and discuss potential future directions.

II. ITERATIVE TBL WORKFLOW IN DATA-RICH ENVIRONMENT

In a typical TBL workflow, students usually start by individually exploring the learning topic as a pre-group activity before transitioning to the group learning phase [3]. Some assessments are also included in this phase to gauge the readiness for group learning. Subsequently, group learning activities commence, encompassing various tasks such as discussions, presentations, and other collaborative work. The former steps can recur several times iteratively, and finally, the TBL concludes with peer evaluations. Figure 1 below illustrates the generic workflow for TBL according to [3].

When implemented in a data-driven environment, the learning log data from previous rounds empowers teachers to deliver targeted interventions [20]. With the increasing accumulation of learning log data, recent CSCL studies have opened avenues for supporting collaborative learning with state-of-the-art technical frameworks and data-rich environments [2]. Group Learning Orchestration Based on Evidence (GLOBE) [37] outlines four phases of collaborative learning for data-driven support: group formation, orchestration, evaluation, and reflection. Compared to the original TBL design, the framework incorporated the peer evaluation phase into the recurring steps, wherein students can assess the products or outcomes of their peers' learning experiences, engaging in a formative reflection process [38]. Digital systems such as group formation and peer evaluation modules within the GLOBE framework facilitated the data flow with AI scaffoldings. As the GLOBE infrastructure matures, LA for group learning, such as algorithmic group formation, can become increasingly automated with the growth of data on group learning performance.

Given this background, we will now introduce data collection opportunities in each phase of iterative TBL throughout the workflow (refer to Figure 2). During the individual learning phase, behavior logs and readiness test scores are collected for each learner. These data can be computed as learner model attributes that depict students' learning characteristics and can be utilized for optimized group formation. In the group orchestration phase, interactions and engagement can also be logged, contributing to group awareness for formative feedback and reflection. Furthermore, teacher and peer ratings and comments are incorporated into the group learning process, serving as evidence of group learning performance. The following section will provide a detailed breakdown of the activity flow within one round of iterative TBL.

A. INDIVIDUAL LEARNING PHASE

As an indispensable preparation phase in flipped learning design, individual preparation holds paramount importance. [39] has pointed out that the individual ideation phase before the group learning starts is significant and can improve the quality of subsequent collaboration. In the team-based learning design, individual learning activities cover pre-reading the learning materials, and pre-test for readiness [5]. During these individual learning activities, learner attributes can be modeled from learning logs and test scores. In a broader view from a data-driven perspective, the data covered in this stage is not confined to cognitive skills but also covers general attributes such as personalities and demographic information from online surveys.

According to research from [40] on cognitive load theory in collaborative learning, antecedents describing all attributes available before the group learning starts can pose an effect on the subsequent phases of collaboration processes and consequences. Therefore, they can be utilized for data-driven support in the group learning phase such as optimized group formation and early detection and intervention for left-behind students.

Moreover, as there are recurring steps as a cycle, the experience gained in group learning during the previous TBL round can significantly contribute to subsequent individual learning rounds. When reflecting on the prior TBL round, learners have the opportunity to recap their group learning experiences, draw lessons from peer evaluations, set goals, and make revisions for improved performance in subsequent

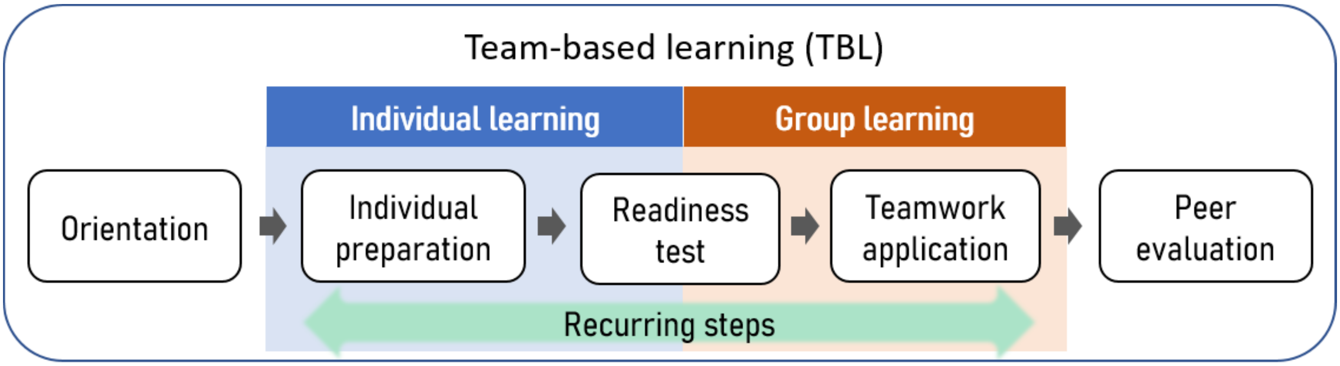

FIGURE 1. Generic workflow for TBL reproduced from [3].

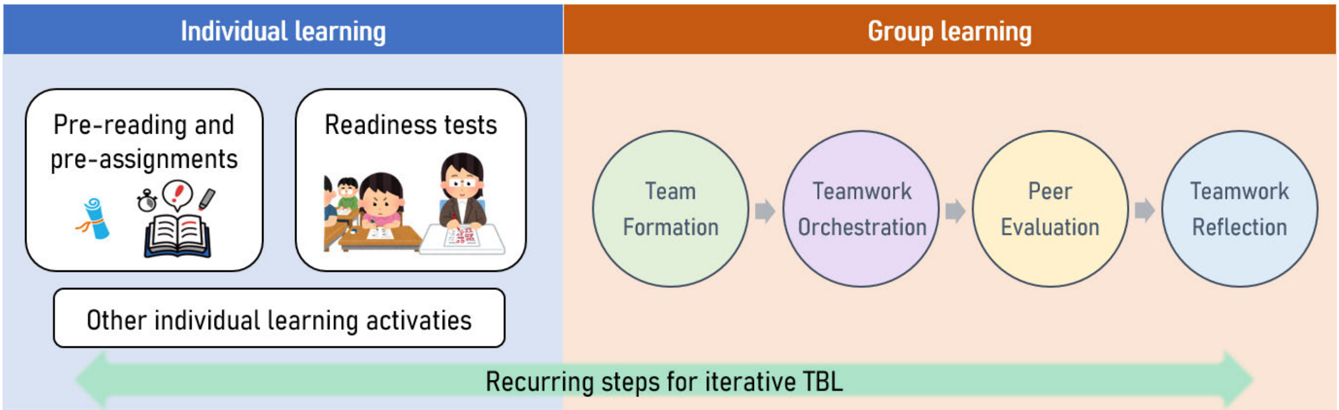

FIGURE 2. Workflow of iterative TBL with GLOBE.

TBL iterations. For instance, collaborative writing tasks and intra-group feedback enhance report writing through effective TBL applications. The collaborative problem-solving approach, where challenging problems are addressed with peer assistance during each group learning round, can support successful problem solving on similar topics during the individual learning phase.

B. FOUR PHASES OF DATA-DRIVEN GROUP LEARNING

When it comes to the group learning phase, Group Learning Orchestration Based on Evidence (GLOBE) [37] presents a framework for AI-based collaborative learning support with data-driven approaches in an LA-enhanced environment. There are four phases of collaborative learning: group formation, orchestration, evaluation, and reflection, where data flow and AI scaffold are empowered by the group formation and peer evaluation modules (see Figure 2). The following sections will further introduce four phases of GLOBE with the continuous data flows among the GLOBE modules.

1) FORMATION

In the broader scope of Computer Supported Cooperative Work (CSCW), research related to group formation revolves around the concept of "studying and designing technologies that bring people together in partnerships, teams, crowds, communities, and other collectives" [41]. In the realm of group learning design, group formation assumes a fundamental role [42]. Traditional grouping strategies like seating students next to each other or spontaneously forming groups have limitations when devoid of data, potentially leading to issues such as excessive homogeneity [43].

Collaborative learning within properly constituted groups surpasses conventional teaching methods [44]. Numerous factors, including the characteristics of group members, the context of the grouping process, and the techniques used to create groups, can influence group learning processes [45]. Among these factors, knowledge holds a prominent position and can be assessed through knowledge test scores and graph-based knowledge models. Nevertheless, beyond ordinal scores, the interrelationships between individuals and their personalities also play a pivotal role in group formation. In data-rich environments, student model data from learning logs allow for the incorporation of student characteristics when forming groups [46]. In Figure 2 of the data flow model, LA for group learning, such as algorithmic group formation, can become increasingly automated as more data from previous group work experiences accumulates.

As per the theory of proximal development (ZPD) [47], it is recommended to compose groups with varying abilities, especially in contexts where mutual assistance is encouraged [48]. Hence heterogeneity often manifests in distinct levels of prior knowledge and cognitive skills. Conversely, fostering homogeneous engagement in learning enhances the quality of group tasks, as well as the interaction and self-efficacy among learners [49], [50]. Homogeneity in this context often pertains to non-cognitive aspects, such as personality and interests.

Manifold techniques are employed for creating learning groups or teams, contingent on different student model data and objectives. One approach for forming groups with disparate abilities involves ranking students based on specific indicators and selecting students from various parts of the distribution [51]. Homogeneous groups are created using clustering techniques founded on distance measurements. For example, the K-means algorithm clusters students with similar attributes [52], [53], while hierarchical clustering aids in group recommendations based on collaborative filtering [54]. In scenarios where students generate substantial learner-created content, semantic methods are utilized to group students based on textual features, considering knowledge diversity, textual similarity, and a semantic network of learners' interaction texts [55], [56], [57]. However, quantifying group heterogeneity with comparable values remains challenging when employing semantic matchmakers [58].

2) ORCHESTRATION

The orchestration phase reflects the process of group learning, which can include assorted activities such as discussions, collaborative working (e.g. programming, knowledge map generation), and presentations. The process data incorporates textual or voice data that depict discussions, video data, and behavior logs in group learning platforms. Effective communication is essential for reflecting interactions among participants, and these interactions can be effectively captured by instrumenting relevant mediums. In the context of online education, online forum discussions have been analyzed using social network analysis techniques [32], [33], [34]. Currently, AI is widely employed to analyze the interactions during collaborative learning. This includes voice processing coupled with semantic analysis, sentiment recognition [37], and the capture and coding of gestures from video data collected during collaborative sessions [59]. Beyond the conventional indicators, behavior logs in group learning platforms open an avenue for interactive logs in computer-supported collaborative learning contexts.

The outcomes of these analyses, often used as indicators of learning performance, can be presented in ways that provide group awareness information on the collaborative process for learners, offering valuable formative feedback [38]. These insights offer transparency, enabling teachers to intervene promptly [60].

Moreover, the data derived from group learning processes can be further leveraged in subsequent phases and rounds within the GLOBE ecosystem. It's important to note that team-based learning encompasses not only group discussions but also programming, workshops, and other collaborative activities, and different kinds of process data can be collected via xAPI statements [61].

3) EVALUATION

The group learning evaluation phase serves a dual purpose, as it can not only assign course grades but also enhance the quality of group learning while motivating individual learners [62]. The evaluation methods can be broadly categorized as summative and formative assessments [63]. Though the original TBL paradigm put peer evaluation as a summative step in the workflow [3], formative assessment has been proven to be highly beneficial for stimulating reflection and immediate corrections [64], [65]. Thus, in data-rich environments, adopting instant feedback [21] and enriched group awareness information [22] is prevalent to support the group learning process.

To bolster peer evaluation with data-driven support, group awareness information is generated based on accumulated learning logs, including forum engagement and knowledge contributions [21]. This information equips raters with more reliable decision-making capabilities. The reliability of peer evaluation can be quantified by estimating peer rating potentials, utilizing student model data from previous group learning experiences, which assigns different weights to ratings based on the reliability of the raters [66]. Furthermore, behavior pattern analysis based on web survey theory can describe the rating behavior patterns [67]. Additionally, natural language AI conversation analysis plays a crucial role in interpreting the quality of written feedback [68].

In parallel, online evaluation systems enable participants to provide feedback to their partners, thus contributing to the modeling of their group work and task experiences [40]. The anonymity offered by online evaluation collectors enhances the reliability of the feedback provided by participants [69]. With the increasing adoption of self-reported evaluation and immediate feedback from actual participants in TBL contexts, coupled with attributes of the group learning process from the previous phase, all this evaluation and feedback data can be synchronized with the student model and subsequently used for various algorithmic grouping purposes within LA [70].

4) REFLECTION

After each round of group learning activities, the data collected during group learning can be organized, structured, and presented to both learners and instructors for reflective purposes. This data encompasses information from the orchestration and evaluation phases, serving to foster social learning among students and provide teachers with valuable insights through simple LA [71].

For instructors, the analysis and visualization of classroom activities are crucial for their professional development [72]. Through data reflection, teachers can access a dashboard that highlights how the class progressed, whether it deviated from the lesson plan during the actual activity, and whether the students were able to follow the TBL activity design [73]. Accordingly, teachers can refine the learning design based on the reflection as professional training.

Additionally, this data can serve as a foundation for creating more advanced evaluation metrics tailored for process-based competency assessments [74]. Reflecting on these performance indicators can motivate students to develop strategies for addressing their weaknesses, actively contributing to their self-directed learning [75]. In TBL, this implementation of formative learning encourages students to apply their acquired knowledge and enhance areas where they may have identified deficiencies during the current round of group learning. This iterative process fosters continuous improvement.

Moreover, the insights from LA research can be harnessed for student modeling, leading to advanced service innovations like AI recommendations to identify determinants of desirable learning performance [19]. This concept can also be seamlessly integrated into the realm of TBL, providing valuable support and guidance to students.

III. STEPS FOR CONDUCTING ITERATIVE TBL WITH DATA-DRIVEN SUPPORT

This section will introduce the iterative TBL framework in a data-oriented perspective. We proposed three major steps of data-driven design of TBL scaffold applications (see Figure 3). It begins with synthesize data created in individual learning activities, collect and utilize log data during the group learning, and analyze data to create intelligent models for LA research.

A. SYNTHESIZE: INTEGRATE MULTIPLE DATA SOURCES FROM INDIVIDUAL LEARNING

The initial stage of data-driven design involves integrating various data sources. The data covers not only traditional test scores but also learning behavior logs from assorted digital platforms. The scope extends beyond learner-knowledge connections, such as the proficiency of each knowledge unit, to include knowledge-knowledge connections, like precedence in the learning order. Meanwhile, the data is not restricted to numerical variables; it includes relationship graphs and interactions in reading activities, like overlaps of annotations. The diverse data sources can be interconnected through Learning Tools Interoperability (LTI) protocols, and learning logs from different platforms can be formatted into xAPI statements. Leveraging the integrated data, learner models can be constructed to depict student characteristics based on their learning behaviors. This integration also facilitates vector-based input for LA algorithms.

B. UTILIZE: COLLECT GROUP LEARNING EVIDENCE FOR THE SUBSEQUENT ACTIVITIES

To overcome cold start problems arising from limited data on learner attributes when a teacher launches a iterative TBL design, especially in offline school contexts, the framework should incorporate the accumulation and re-use of data during TBL. This aspect is often neglected in current CSCL research. Therefore, it is essential that each technical intervention tool employed in the TBL design not only consumes data but also serves as a sensor of meaningful learning behaviors. Within the aforementioned data-driven iterative TBL framework, the framework not only leverages learning log data from other platforms but also actively collects data during the group learning phases. These data offer insights into group learning performance, enhancing the modeling of collaborative skills among learners. For instance, engagement data, such as the number of utterances and meaningful tokens, and the equivalence of participation, can reflect a learner's collaborative skills. Through multiple rounds of group learning in iterative TBL, learner model attributes related to group learning can be constructed for subsequent group learning tasks and other LA applications.

C. ANALYZE: DISCOVER NEW PROSPECT IN GROUP LEARNING

Over multiple TBL rounds, data can be collected and subjected to analysis within an analytics engine for model creation. Identifying struggling students from learning logs and recognizing behavior patterns for targeted interventions are frequent in LA studies. For instance, evidence from a sufficient volume of training data can be harnessed to predict successful group work and enable early identification of at-risk students, particularly within flipped learning contexts. Moreover, if the process of extracting models from evidence can be automated, the dynamic recommendations for optimal group formation settings for specific contexts or purposes, based on continually updated data, become a promising prospect. Guided by analysis outcomes, context-based group formation with less parameter setting work can alleviate teachers from the trivial task of manually creating groups, empowering them to focus on other aspects of instruction.

IV. EXAMPLES OF ITERATIVE TBL WITH DATA SUPPORT

In this section, we illustrate two typical tasks that underscore the significance of data-driven support in iterative TBL. These cases specifically center on the group formation and group work evaluation phase, two aspects that have received less attention in related studies on CS-TBL. One of the goals of presenting these studies is to prompt research on phases before and after the ongoing orchestration phase of teamwork, which also deserves data-driven attention. The first task involves algorithmic group formation using learning log data, and the second task pertains to the early detection of peer evaluation reliability.

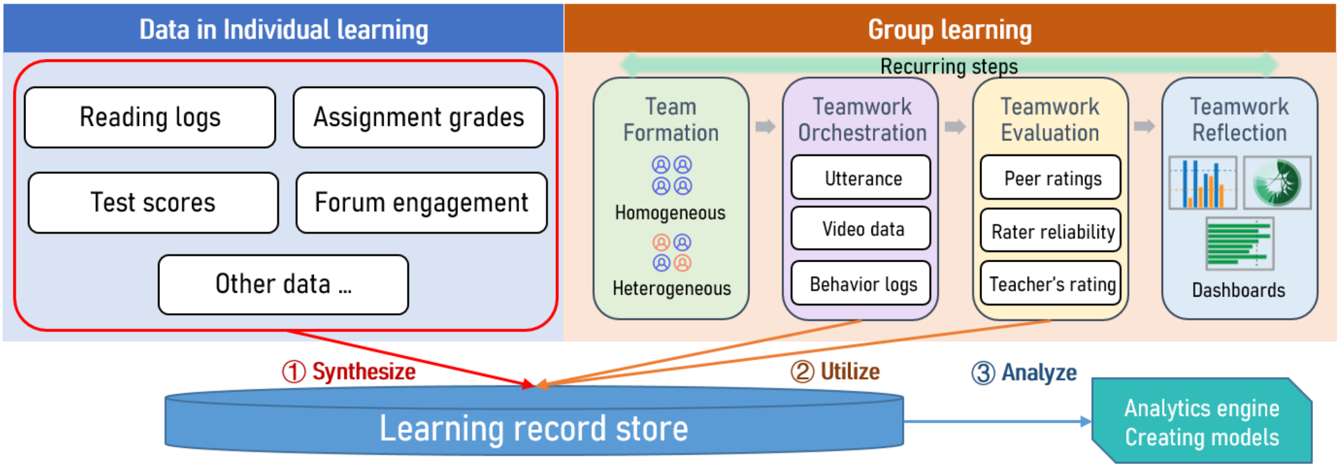

FIGURE 3. Data flow of iterative TBL with GLOBE.

A. OPTIMIZED GROUP FORMATION

In this case, learning log data from the individual learning phase of TBL are integrated to create groups, and the group learning process and outcome of the current activity will be collected and re-used for group creation in the subsequent rounds. Meanwhile, indications with colors based on previous round performance are shown to teachers for the intervention of endangered students and groups. Finally, the accumulated evidence can be used for data analysis to create prediction models of successful TBL.

The data-driven implementation of algorithmic group formation follows three steps of synthesizing, utilizing, and analyzing data, following the data flow in Figure 3. Firstly, a system using genetic algorithms is designed and implemented to form groups using learning log data from various data sources. In terms of data synthesis, the presented group formation system enables student models from different data sources underpinned by genetic algorithms and LEAF infrastructure that aggregates multiple learning logs [76]. These logs cover online reading logs for engagement and annotation behaviors, quiz scores from the LMS, uploaded offline test scores (performance data), survey responses (perception data), and so on. They are synthesized into a comprehensive platform and standardized for group formation. Meanwhile, previous forum engagement data and peer rating data indicating the group work experience are collected and can be leveraged for subsequent rounds as well, which happens in the utilization step.

To represent a group formation, one combination of students constructs a candidate individual (G) as a set of randomly-ordered students (s) partitioned by groups (Figure 4(b)). To synthesize multiple data sources, there is a corresponding vector covering different characteristics of each student for the calculation of fitness value (Figure 4(a)). Each dimension of a student vector is represented by a certain variable selected by the user. Figure 4(a) illustrates an example of metrics representation where each student (s) is represented by a column vector with a characteristic (c) as a dimension. Students are allocated into groups through iterative processes from the first candidate individual (G) with a genetic algorithm [77]. Beyond rankable scores, the algorithm can consider relationship data describing positive or negative connections between participants and annotation data of common markers.

Secondly, As for data utilization, the continuous data-driven support provided throughout the two phases of GLOBE is summarized in Figure 5. A simple randomized grouping followed by using evaluation scores for subsequent grouping provides a feasible solution to the cold start problem in data-driven research [78]. As shown in the figure, the peer and teacher evaluations are logged into the learning record store as part of the student model (orange circles) and can be reused as input to the algorithm in the following group formations (orange triangles). These inputs can also identify students who may need special attention in the current group learning beforehand [79] in the detail panel. At-risk students and groups can be alerted in the instructor's panel, indicating that they need more attention from the instructor. Furthermore, by utilizing accumulated group learning evidence in the GLOBE ecosystem, predictive group formation indicators were explored that can enable automatic group formation based on teachers' objectives in different contexts for desirable performance in subsequent group learning activities.

Further, the former two steps of data synthesis and utilization have been implemented in authentic classes. These studies encompass a range of learning contexts, spanning from primary school to higher education levels. Take an academic reading course in higher education as an instance. In this course, TBL design was conducted several times from week 3 to week 11 across the 15-week semester [80]. Following the iterative TBL framework, students went through the workflow of the weekly activity shown in Figure 6. In individual learning, students read

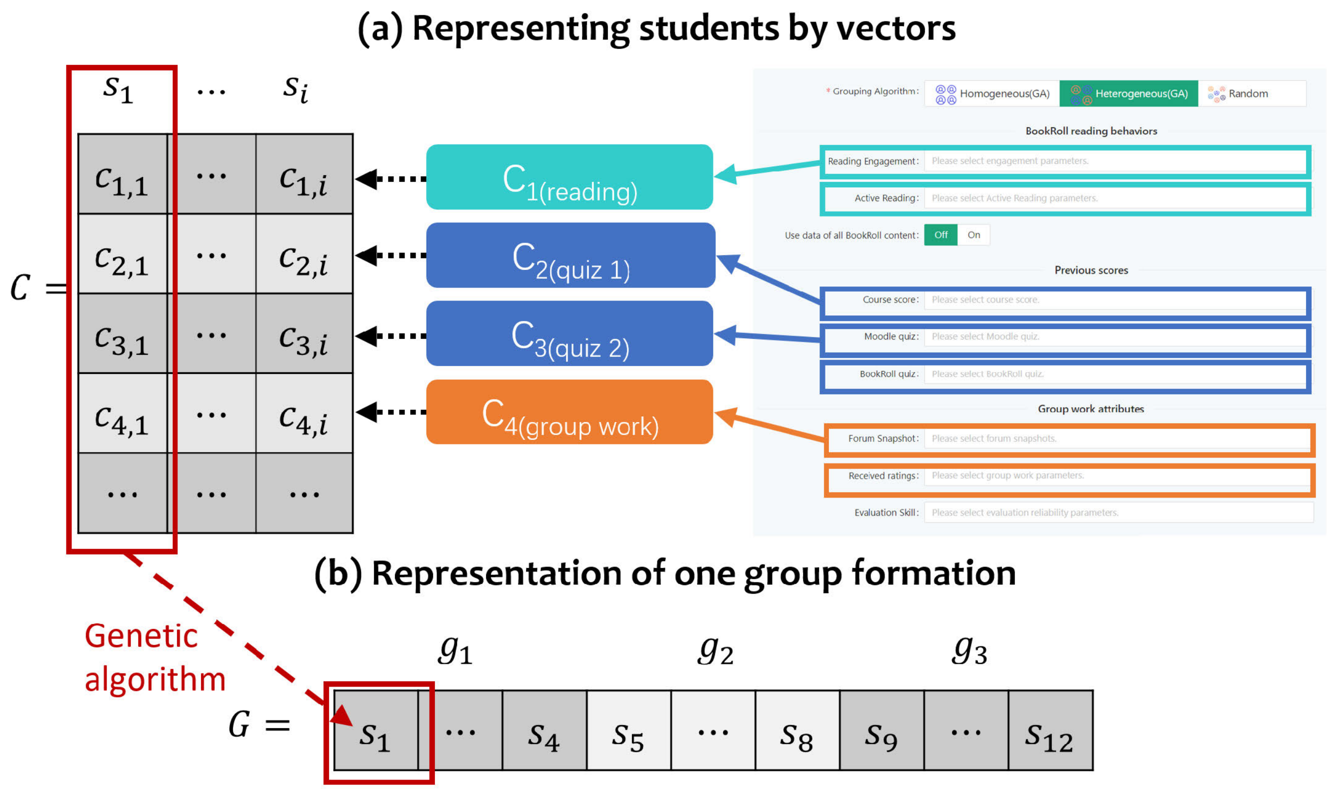

FIGURE 4. Algorithmic group formation based on multiple learning log data.

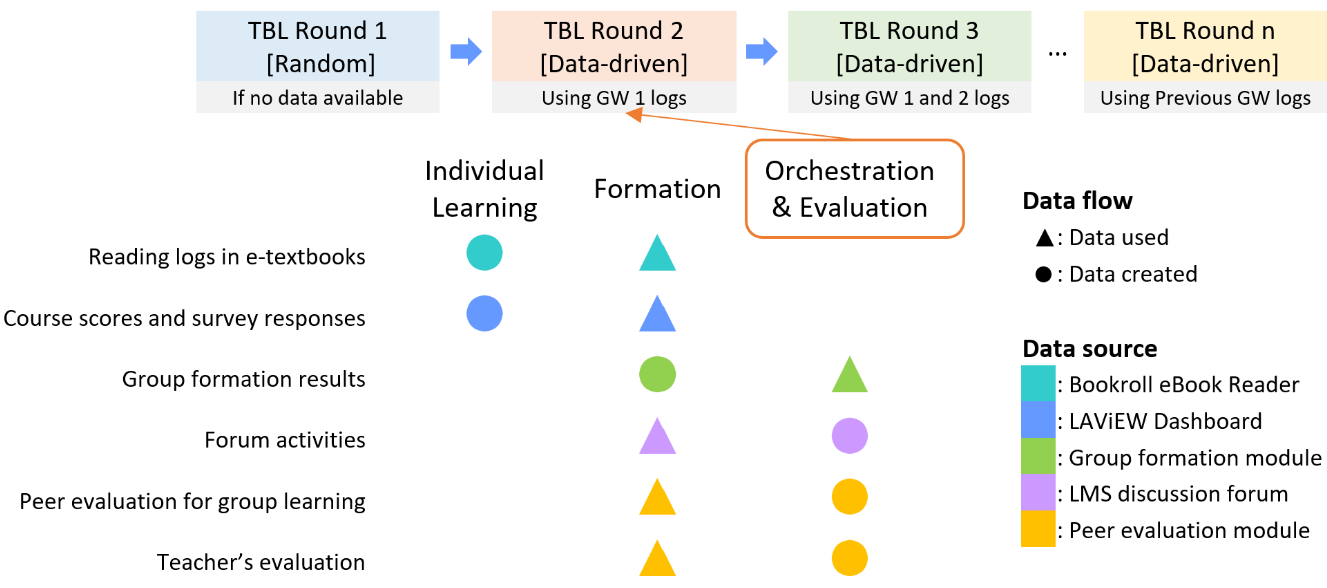

FIGURE 5. Continuous data feedforward for group formation function.

several articles on BookRoll, an e-book reading system that can automatically collect learning data. Then, in the group learning phase, they should share and discuss their reading progress with their group members in the Moodle forum and prepare a brief presentation as a group for the next offline class. During the class, each group made presentations, which were peer-evaluated by the audience (both the instructor and students) in the classroom in the evaluation systems. In the meantime, they made peer ratings on the initiative and communication of their group mates in the peer evaluation

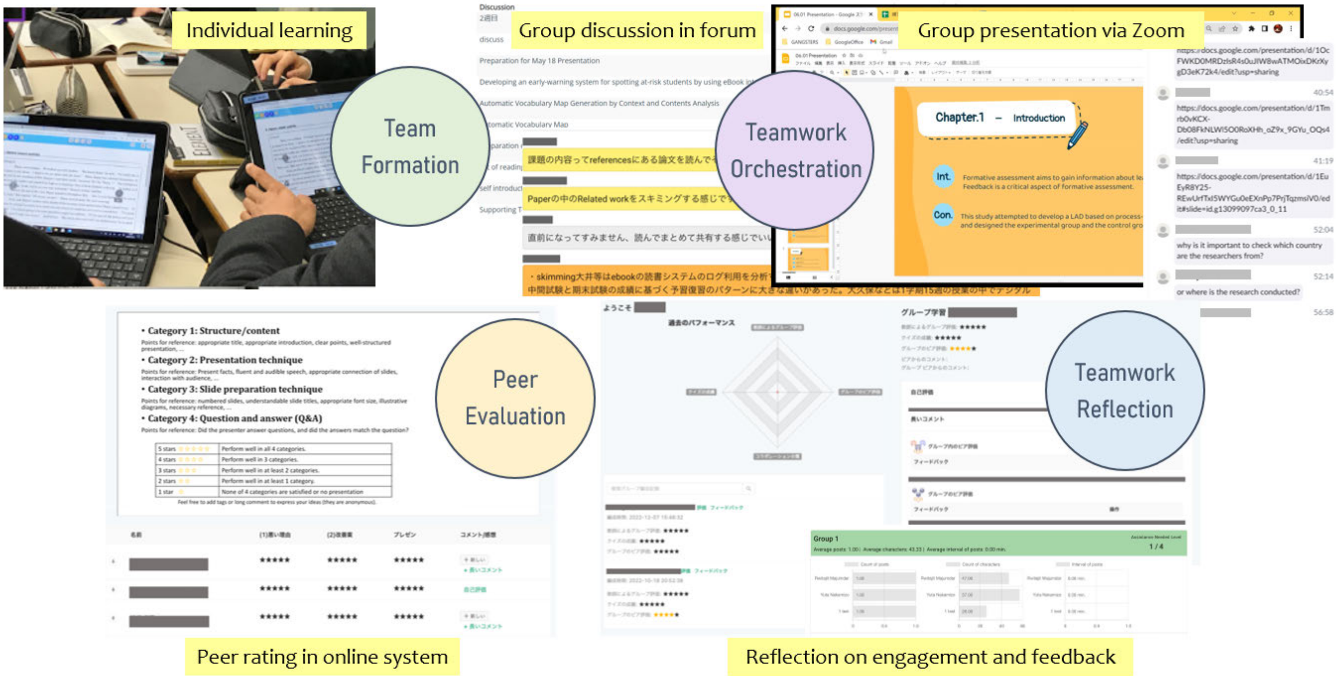

FIGURE 6. **Workflow of iterative TBL implemented in the academic reading course.**

system for each week as well. They can check the forum engagement dashboard and feedback from classmates for reflection, which can help them improve for the subsequent round.

Building upon the accumulated evidence, data analysis was conducted to investigate predictive indicators of group formation in specific contexts. From a preliminary correlation analysis within a reading-based group learning environment. The results revealed that individual achievement in group work can be inferred from reading engagement and previous peer ratings. Moreover, a homogeneous grouping strategy based on reading annotations and prior group work experience can forecast favorable group performance in this particular learning context.

B. RATER RELIABILITY IN PEER EVALUATION

To evaluate TBL, teacher evaluation is typically summative, while it has limitations since one teacher cannot monitor all group activities simultaneously [16], [18]. Moreover, issues like social loafing and free-riding pose significant challenges to effective TBL [63]. Thus, peer evaluation becomes crucial to alleviate the teacher's workload and provide real-time insight into the group learning process [81]. Considering the developmental stage, cognitive abilities, and social dynamics of learners [82], peer evaluation activities are more suitable for higher education settings. Nevertheless, implemented in younger learners in junior high school [83], with the national guidelines encouraging interaction among learners in K12 education [84]. However, it's essential to provide clear rubrics and articulate evaluation criteria in an understandable manner for the target learners to enable broader implementation [85], [86].

In peer evaluation, students provide ratings and feedback on each other's work, which is formative and can enhance their performance in subsequent tasks [38]. However, peer evaluation reliability is a significant concern, as the quality of peer evaluation remains promising [65]. Recent studies have introduced strategies to enhance the reliability of peer assessment. These strategies include focusing on privacy protection [69], providing group awareness support as decision-making assistance [18], [21], and implementing interactive peer evaluation platforms with backward feedback mechanisms [87].

Nonetheless, issues of unbalanced grader reliability due to individual differences among learners persist, leading to less accurate evaluation results in practice. Some students do not take the task of evaluating others' work seriously, rushing through the rating process and providing uniform scores. This phenomenon is problematic, as obtaining fair and constructive feedback is crucial in collaborative learning. To address this problem, researchers have attempted to adjust the final rating values based on grader-specific variables, such as previous rating tendencies [88] and previous grades for relevant tasks [66], [89]. However, the potential of using learning data in digital systems has been underutilized, limiting the comprehensive consideration of these variables in existing peer evaluation designs.

To address the issue of rater reliability in peer evaluation, data-driven support for the peer evaluation phase of TBL can follow three steps mentioned in the previous section.

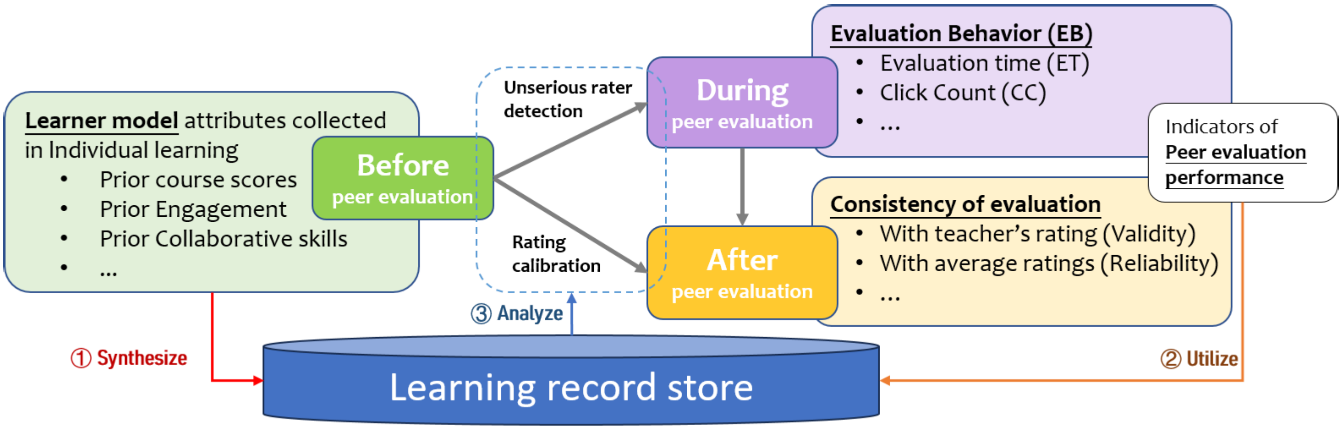

FIGURE 7. Data-driven design of peer evaluation studies.

Figure 7 illustrates the data-driven design of peer evaluation studies. Learner model attributes, which encompass all data collected during the individual learning phase and depict learner characteristics, have the potential to improve rater reliability in peer assessments [66]. Therefore, this data is synthesized into rating potential indicators, with specific weights fine-tuned for each learner model attribute. During the group learning phase, this case places a focus on the dynamics of the evaluation phase, examining peer evaluation behaviors in online systems. Concurrently, consistency measures for each rater are implemented, indicating the deviation between rating scores from experts (instructors) and from the average level. The data gained from the peer evaluation activity are then re-utilized in the next round of TBL for analysis. Potential topics for data analysis include the early detection of unserious raters before the peer evaluation activity and the calibration of final scores received by each learner.

Consider the case of early detection of unserious raters, as introduced in [90]. This study takes place in a higher education design course implementing a team-based learning design. The peer evaluation activity entails rating group presentations, focusing on interpretations of ''good and bad design'' using knowledge from weekly lectures on concepts in interaction design. Throughout each week of the experiment, a new-topic lecture was provided through an e-book platform before class. Individual learning included reviewing lectures, participating in forum discussions, and summarizing assignments. Within the group learning activities, students engaged in group sharing of the previous week's assignments. They presented outcomes from their forum discussions in jigsaw groups. In these jigsaw groups, peer ratings were assigned to individual presentations, facilitated by the peer evaluation system. In the final week, students worked in groups to prepare a final presentation summarizing their learning, which they delivered in class. The behavioral pattern analysis in this study is rooted in the peer evaluation of these concluding presentations.

Drawing from an earlier model of evaluation behaviors [91], six feature variables were proposed to identify indicators of poor feedback quality. These variables encompass two constructs: time features and scoring features. Principal Component Analysis (PCA) was employed to distill these constructs from the original dataset, capturing the nuances of rating behaviors. The subsequent cluster analysis revealed that unserious evaluators tended to rate quickly and assign uniformly high scores. The study's second objective was to explore whether cases of unserious ratings could be detected before the final evaluation round. Several classification methods were compared in how well they could predict whether a student would end up in the serious or unserious rater cluster. The predictor variables were taken from previous evaluation rounds and incorporated data related to individual learning, including reading engagement and forum participation. The results demonstrated that using five or more predictors and applying logistic regression or a neural network analysis led to classifications that were approximately 70% accurate. Within this learning scenario, the evaluation behavior in the preceding rating round and reading engagement appeared to provide significant information gain. In contrast, rating behavior in the initial round and forum participation exhibited weaker predictive power.

V. DISCUSSION

By addressing the broader discussions on data-driven iterative TBL designs, we identify several key areas for future investigation based on the results of the topical review. These include the development of data infrastructure, addressing privacy concerns, assessing the applicability across educational contexts, facilitating field implementation, evaluating the effectiveness, and ensuring explainability.

A. DATA-DRIVEN INFRASTRUCTURE

The diversity of data available throughout TBL underscores the significance of a data-driven infrastructure. However, not all regions possess existing infrastructure with multiple learning log data available for analysis [92]. Some issues may stem from policy constraints related to strict privacy laws, while others could be attributed to cold start problems. In the latter case, the importance of launching data sensors is vital to initiate data-driven circulation. As suggested in the previous discussions, LTI and xAPI provide a technical grounding for data collection and a pipeline for cross-system exchange in digital educational environments.

B. ETHICAL ISSUES AND PRIVACY

Challenges related to data usage, particularly ethical concerns, data privacy, and policies on personal data, should be addressed when designing data-driven services [93], not only for TBL but for all practices concerning educational data. For example, GDPR in Europe calls for a high level of personal data protection, increasing the difficulty of learning data aggregation in the synthesis phase. Therefore, data-driven services need to align with the policies of different regions to uphold human rights. To obtain full ethical approval, explanations to the involved students and parents regarding the research purpose, data collection, and utilization are indispensable to follow the ethical committee's rules. Meanwhile, the database design and pipeline should prioritize concerns related to anonymity, where only the anonymized data omitting the personal information can be extracted from researchers [94]. This is equally crucial for user-end services that contain sensitive personal data, such as peer evaluation systems, where the visibility of peer rating scores requires careful consultation with teachers based on educational scenarios [95].

C. IMPLEMENTATION OF DATA-DRIVEN SERVICES

Implementing data-driven support for authentic teachers and students in real classrooms poses challenges, necessitating attention to the curriculum design of TBL and the unfamiliarity of school teachers with digital systems. Hence, it is a prerequisite to understand the teacher's needs and educational gaps. For instance, in group formation, creating groups with learners who share similar strengths and weaknesses enables focused attention on common challenging areas or enhancement of proficiency in specific domains. However, the traditional practice of creating such groups in everyday classrooms involves time-consuming tasks like administering pre-tests and aggregating data. Here, data-driven services prove pivotal. Notably, positive feedback from teachers underscores significant time savings in the streamlined group formation process, reducing it from 1 to 1.5 hours to approximately 30 minutes [37], thereby reducing the barrier to incorporating group learning into everyday classroom activities.

Moreover, in practical curriculum design, the workflow of data-driven iterative TBL exhibits flexibility to adapt to various learning scenarios. The order of individual learning and group learning phases is not strictly divided and can be intertwined in each round of implementation, as the key issue remains to address the real needs of educational practitioners through appropriate data support.

As contexts affect activities, the application of iterative TBL should also adjust depending on the developmental stage and cognitive capability of the target learners. For example, as peer evaluation activities are typically implemented in higher education [82], applying them in primary education may require more effort in clarifying rubrics and criteria to help students understand their responsibilities, potentially encountering more obstacles. To enable flexibility across different contexts, data-driven services can not only offer advantages over laborious manual processes but also provide an intelligent platform for effortless manipulation by recommending settings, as seen in the group formation case [80]. This capability allows educators to experiment with diverse grouping conditions based on data-driven recommendations aligned with their objectives.

D. EVALUATION OF DATA-DRIVEN INTERVENTIONS

Understanding educational contexts is also crucial for data-driven designers evaluating TBL. Solely assessing performance from an algorithmic perspective may lack pedagogical foundations. When evaluating a group formation system, considerations should go beyond achieving accurate figures and the best-optimized solution, and factors like time sacrifice matter. In educational implementations, relatively optimized output can be acceptable, especially considering the importance of speed highlighted by frontline teachers [13]. Consequently, co-designing with educational practitioners is crucial to understanding actual demands and what should be considered in empirical studies. The evaluation indicator design should based on the educational purpose [74].

Designing the evaluation approach is also a promising task. Although traditional approaches like grading from teachers and peer evaluations can reflect the performance and effectiveness of TBL, they tend to be subjective and summative. Hence the accuracy of the evaluation indicator is another concern, as peer evaluations can be deliberately crafted or influenced by unserious raters. As discussed in the aforementioned case, data support, such as using learner model attributes to predict those prone to free-riding with social loafing, enhances the grounding of the evaluation ecosystem in data-driven TBL.

E. EXPLAINABILITY OF TECHNIQUES

When evaluating TBL through objective behavior logs, like group work dynamics and social network graphs, it becomes evident that these logs can effectively depict learning patterns and provide formative group awareness information. However, a significant challenge lies in the explainability of data-driven AI tools, especially in emerging AI areas. From an algorithmic perspective, it is crucial to enable teachers to understand the output of data-driven tools with clear justifications for AI-generated outcomes [96], an aspect that is not extensively discussed in existing studies. In contemporary applications, there is a growing reliance on "vector embeddings" (of texts, graphs, images, etc.) in combination with neural networks and deep learning techniques, replacing original data structures. While vector embeddings may not be lossless, the hope is that they preserve structural properties essential for interpretation, bringing this aspect back into the educational discourse. In the example of group formation, a detailed dashboard is provided for teachers, illustrating the distributions of each learner's model attributes from individual learning. This feature enables teachers to easily grasp the heterogeneity in group formation inputs within each group. This case exemplifies efforts toward the explainability of data-driven developments involving complex algorithms.

VI. CONCLUSION

In conclusion, our topical review contributes to advancing the understanding and utilization of data-driven approaches in iterative TBL scenarios. To overcome challenges such as cold start and data re-usage in current data-driven TBL implementations, we propose a data-driven iterative TBL framework, rooted in the GLOBE framework for data-driven group learning. This framework incorporates all phases of TBL, comprising four distinct phases of group learning activity workflow and three essential steps of data flow. It serves as a guideline for implementing data-driven support in iterative TBL contexts and also contributes to a taxonomy for existing literature in this field for a better understanding of its current status.

Through the examination of two instances—algorithmic group formation and peer evaluation reliability assessment—we demonstrate the potential efficacy and authenticity of data-driven approaches in improving TBL outcomes. These instances also highlight research opportunities in phases preceding and succeeding the ongoing orchestration phase of group learning, which deserve further exploration in future studies. Moreover, these cases not only demonstrate the application of our framework but also offer valuable insights for future research and development, including sample workflows for activity and technical designs.

Moving forward, our paper aims to establish an ecosystem conducive to data-driven collaborative learning. This ecosystem seeks to empower both educators and learners with actionable insights derived from data-driven interventions, fostering effective collaborative learning designs, and ultimately optimizing collaborative learning experiences through data-driven services.

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