# Formative assessment of group work skills: An analytics-enabled conceptual framework

**Natasha Arthars, Kate Thompson, Henk Huijser, Steven Kickbusch, Samuel Cunningham, Gavin Winter, Roger Cook, Lori Lockyer**
Queensland University of Technology

Assessing group work formatively in higher education poses a significant challenge. The complexity of evaluating individual contributions is compounded by the lack of efficient and effective methods for tracking, analysing and assessing individual engagement and contributions, which can impede timely feedback and the development of group work skills. This paper contributes to the growing body of research on collaboration analytics, which focuses on learning analytics (LA) in collaborative settings, and formative assessment while providing practical guidance for educators seeking to enhance formative assessment practices. The potential enhancement lies at the intersection between analytics technology and assessment design. In this paper, we present a conceptual framework that can harness multimodal data collection as well as LA to formatively assess and provide feedback on individual engagement and contributions to group work across physical and digital spaces. Drawing on research that considers design for learning, conjecture mapping, assessment design, multimodal LA and feedback, we outline a structured approach to developing formative assessment of group work skills in collaborative projects and higher education contexts.

*Implications for practice or policy:*

- Practical guidance is provided for educators to enhance formative assessment practices with LA.
- The integrated framework and process offers a guide for formative assessment in group work scenarios, providing tools for monitoring student progress, informing pedagogical decision-making and enhancing learning experiences.
- The integration of the activity-centred analysis and design framework and LA allows educators to harness the power of both data-driven decision-making and learner-centred pedagogical approaches to better support learner development in group work settings.

*Keywords*: group work, learning analytics, formative assessment, collaboration analytics, activity-centred analysis and design (ACAD) framework

## Introduction

In Australia's higher education (HE) landscape, the emphasis on graduate attributes has never been more pronounced. Many universities and tertiary institutions have recognised the multifaceted demands of the 21st-century workplace and have prioritised the development of a diverse range of competencies in their graduates. Central to these competencies is the ability to work collaboratively in groups (Oliver & Jorre de St Jorre, 2018; Worsley, Anderson et al., 2021), a set of skills that mirror the dynamic and interdependent nature of modern work environments. As group work becomes an integral component of HE curricula (Forsell et al., 2021; McConnell, 2005), there is increasing potential for formative assessment to guide and enhance collaborative learning experiences.

A key challenge in formative assessment lies in its inherent complexity. Formative assessment necessitates ongoing evaluation and feedback throughout group work, demanding consistent attention and considerable effort from both teachers and students. Such an investment of time and resources can be demanding, particularly in settings with large student populations (Afzaal et al., 2021). Moreover, with the advent of advanced technologies, including generative artificial intelligence tools used by students, a new dimension of complexity arises (Thompson et al., 2023). These technologies both augment and challenge traditional assessment paradigms, compelling a shift from evaluating the final product to understanding the collaborative process (Rasul et al., 2023). The collection of big education data and the generation of learning analytics (LA) are promising approaches to better track, interpret and understand collaborative processes. However, the integration of digital tools and LA for formative assessment introduces further complexity and challenges such as capacity-building for teachers and students, misalignment between LA and the outcomes they intended to measure, and data privacy and security (Sharma & Giannakos, 2020).

Despite these challenges, the opportunities that formative assessment offers for the development of collaborative group work skills supported by LA are substantial. At its core, formative assessment enables a shift from a product-oriented to a process-oriented view of learning (Maki, 2023). It provides a continuous stream of feedback, allowing students to understand their learning process better and adjust their strategies for improved outcomes. Incorporating digital tools in formative assessment extends these benefits further by providing a rich and nuanced perspective of student learning. Digital tools can track and analyse a vast array of data from diverse learning interactions, offering deeper insights into learning behaviours and outcomes. They can deliver feedback in real time, enhancing its immediacy and relevance. These tools also present opportunities for personalising learning experiences, promoting collaboration and augmenting educational innovation.

However, a pervasive issue exists. In HE, although students are expected to be adept at collaborative group work to become productive learners, these and other important attributes are not always explicitly taught (Jones, 2009). Formative assessment practice is often considered to be less important than summative assessment, which is necessary for the confirmation of a degree (Boud, 2009). This poses a significant challenge: how do teachers effectively assess, guide and refine these group work skills if they are not a focal point of the curriculum? The evolution of formative assessment practices that utilise big educational data LA to provide feedback on the development of collaborative group work skills means that “the technology plays a significant role in shaping the nature of their interactions with each other and supporting their collaborative activities” (Goodyear et al., 2014, p. 440). Design for learning, and assessment design are therefore key to ensuring that students are provided with opportunities to engage in productive social interactions (Goodyear et al., 2014). This led us to the research question central to this article: How can we use LA for the formative assessment of collaborative group work skills?

In this paper, we present a conceptual framework that can harness multimodal data collection as well as LA to formatively assess and provide feedback on individual engagement and contributions to group work across physical and digital spaces. We synthesise research across collaborative learning, formative assessment and LA outlining connections between these key areas of research. We highlight important design considerations arising from the intersection of collaborative learning, formative assessment and LA. These considerations inform a process to create formative assessment for the development of group work skills in HE contexts with minimal or no supervision for collaborative projects using big educational data and LA. In particular, we outline ways in which individual contributions to group work are tracked and analysed in order to be used for formative assessment.

## Background

### Collaborative learning and group work skills

Collaborative learning is an educational approach wherein students work together in groups to discuss concepts, solve problems, or create projects (Qureshi et al., 2023). Rooted in social constructivist theory, it underscores the belief that learning is a deeply social process, where knowledge is constructed through interaction, debate and mutual cooperation. Through this approach, students actively engage with content, peers and their environment, constructing knowledge that is deep and enduring (Kaliisa et al., 2022). Reported benefits include fostering critical thinking, enhancing problem-solving abilities and promoting a deeper understanding of subjects (Balasooriya et al., 2016; Hamer & O’Keefe, 2013; Michaelsen & Sweet, 2008). These skills encompass a diverse range of competencies required to work effectively within a team, such as effective communication, conflict resolution, task delegation and shared responsibility (Worsley & Ochoa, 2020). In HE, where group projects and assignments are increasingly common pedagogical approaches, these skills become imperative. They enable the smooth functioning and success of group tasks and they mirror real-world professional scenarios where collaboration is key. Mastery of group work skills, therefore, extends beyond academic contexts, preparing students for the challenges of professional teamwork, leadership and collaborative problem-solving (Crisp & Oliver, 2019). These skills can be cultivated and refined through guided experiences and reflective practices within educational settings.

Despite its prominence in HE (Forsell et al., 2021; McConnell, 2005), group work presents complexities in formative assessment due to diverse interaction patterns and contributions from students. The fluidity of roles within group work in learning situations further adds to this complexity. Although roles may be pre-defined, similar to professional settings, they may also be emergent and evolve based on the group's needs (Strijbos & De Laat, 2010). There is also significant debate about the level at which assessment takes place in relation to individual contributions or group processes and products (Stahl, 2010). Assessing individual contributions can be challenging for emergent roles, which may vary in scope and complexity, be weighted differently and may shift over time, while the participative behaviours of group members can further complicate fair evaluation of effort and impact across the team (Strijbos & De Laat, 2010). Despite formative work related to the processes of learning (Maki, 2023; Reimann et al., 2009; Shin et al., 2020; Thompson et al., 2013), much collaborative learning research has been directed towards assessing learning outcomes based on the final group work product, rather than formative assessment of individual contributions within these collaborative learning environments.

To address this imbalance, a key consideration in this work is the concept of “collaboration literacy”. Worsley and Ochoa (2020, p. 55) defined this as:

> The ability to ascertain and respond to changes in the quality of a collaborative experience. From the student perspective this amounts to being conscious of one’s own contribution to a group, as well as the awareness and ability to intervene in order to ensure a strong collaboration. From the teacher perspective this includes awareness of how different groups are progressing, being able to respond to those groups in a timely fashion, and developing prompts and activities that afford good collaboration.

Our approach seeks to facilitate development of collaboration literacy, which, in turn, augments students’ participation and effectiveness within group projects. An important part of this approach involves collecting data on student contributions to group work. Factors to be considered in data collection related to collaboration literacy include climate, communication, compatibility, conflict, context, contribution and constructiveness (Worsley, Anderson et al., 2021).

Although understanding and cultivating these skills is essential, identifying a comprehensive and definitive list of the skills required for productive group work is challenging. Skills may differ across scenarios, dynamics, circumstances, education stages and demographics (Brandler & Roman, 2015). More pragmatically, focusing on observable learner actions – such as behaviours, completed tasks and interaction quality – can offer measurable insights into these skills. These might serve as proxy measures for the skills, allowing easier identification (Wong & Chong, 2018) and analysis. However, proxies must be considered cautiously as there is potential for misinterpretation if correlation between learner actions and group work skills is not readily discernible.

### Formative assessment and collaborative group work

Formative assessment has several purposes, including promoting learning, providing diagnostic information and allowing students to understand strengths and areas for improvement (McCallum & Milner, 2021). Formative assessment, rooted in the principles of continuous feedback and iterative adaptation, promotes enriched learning experiences (Black & William, 2009). The underlying principles focus on learner autonomy and encouraging individuals to continually refine their knowledge and skills through feedback. Formative assessment is a multifaceted and interactive practice that perceives teachers, students and their peers as active decision-makers within the learning environment (Black & William, 2009).

A key consideration that should be more prominent in the formative assessment literature in relation to collaborative group work is the inferential nature of the process. Formative assessment extends beyond merely gathering and interpreting evidence. It involves forming conjectures or formative hypotheses about students' skills based on observable factors such as participation and contribution to group work (R. E. Bennett, 2011). The efficacy of these conjectures is strengthened when consistency is observed in student behaviour across multiple sources, occasions and contexts. Ensuring individual accountability is crucial for constructive and meaningful formative assessment. It allows for a precise evaluation of students' contributions and instils a sense of responsibility within the team (Davies, 2009). Methods to enhance individual accountability include clear task definition and performance expectations as well as regular check-ins and peer evaluations (Briscoe, 1994). These strategies foster responsibility, effective communication and objective assessment, thereby enhancing formative student assessment and learning (McMillan, 2014). However, a key challenge is creating visibility around individual contributions without undermining the cooperative essence of group work.

The assessment methods used for collaborative group work in HE settings face certain practical limitations that pose a challenge in accurately evaluating individual contributions (Sprague et al., 2019). Peer and self-evaluations are formative assessment tools which have demonstrated positive effects on student learning, such as increased engagement, improved critical thinking skills and enhanced ability to assess one's own work (Fallows & Chandramohan, 2001; Ibarra-Sáiz et al., 2020; Li et al., 2020). However, there are inherent drawbacks to relying solely on group-level assessment. This approach often fails to distinguish between individual members' efforts, potentially rewarding free riders and penalising hardworking students (Weaver & Esposto, 2012). Consequently, it is imperative to develop improved strategies and tools that can effectively evaluate each student's contributions within group work, thereby making their efforts visible and acknowledging individual contributions.

Feedback, a cornerstone of formative assessment, serves a formative function only when used by learners to improve their performance or learning strategies (Carless & Boud, 2018). In the context of group work, feedback can be targeted both at the group as a whole and at individual students, furthering the impact of formative assessment in enhancing learning outcomes. When integrating LA into formative assessment, it is important to consider who (e.g., individual students, groups or the entire classroom) could benefit from the feedback as well as how they might potentially utilise this feedback (Wise et al., 2023). To maximise the effectiveness of LA-driven feedback, it is vital to carefully design it to ensure it is pertinent and actionable.

## LA for formative assessment and collaborative group work

LA has been defined as the process of "measurement, collection, analysis, and reporting of data about learners and their contexts", aimed at enhancing understanding and optimising learning environments (Siemens et al., 2011). Initially focusing on log data from learning management systems to decipher learner engagement patterns (Bartimote et al., 2018; Gašević et al., 2016), the field has evolved significantly, incorporating theories and methodologies from various disciplines (Gašević et al., 2015). This progression has not only expanded the application of LA across various educational settings (Howard et al., 2018; Lockyer et al., 2013; Martinez-Maldonado et al., 2018; Oviatt & Cohen, 2014) but has also underscored the symbiotic relationship between analytics technology and assessment design. At this intersection lies the potential for enhancements in understanding and optimising both individual and collaborative learning environments, marking a significant shift from traditional analytical approaches to a more integrated, theory-informed practice.

In formative assessment, LA, enriched with machine learning, can offer deep insights into group dynamics and augment peer feedback (Hu et al., 2022; Spikol et al., 2018). These approaches, utilising tools such as social and epistemic network analysis (Buckingham-Shum et al., 2019; Sun & Theussen, 2022), text classifiers, machine learning neural networks and multimodal analytics (Blikstein, 2013), have been employed to support learning tasks and improve assessment validity, offering a pathway to detailed, real-time formative feedback (Aljohani & Davis, 2013; Raković et al., 2023). Moreover, the concept of multimodal learning analytics (MMLA) expands the sources of data to include various modalities with sensors capturing ecological aspects of collaboration (Blikstein, 2013; Schneider et al., 2021). MMLA has been strongly connected to the study of collaboration and triangulating various modalities (Worsley, Martinez-Maldonado, & D'Angelo, 2021). Collaboration analytics provides opportunities for both educators to understand how students collaborate and for students to collaborate more with their peers (Schneider et al., 2021).

Recent advancements, such as the work of Buckingham Shum et al. (2019), Echeverria et al. (2019) and Echeverria et al. (2022), have introduced new dimensions to the application of LA in teamwork settings, focusing on collocated, embodied teamwork in healthcare simulations. They highlight the value of multimodal matrices and automated analytics workflows for providing timely, contextually rich feedback, introducing the concept of "collaboration translucence". This approach, building on Goodyear and Carvalho’s (2014) activity-centred analysis and design (ACAD) framework, seeks to shed light on the physical, social, epistemic and affective aspects of collaboration.

Despite these advancements, translating the potential of MMLA into practical applications in authentic education settings remains a formidable challenge. Martinez-Maldonado et al. (2023) noted the scarcity of MMLA studies conducted in the wild (i.e., under authentic conditions) that close the LA loop by providing feedback to students directly using visual interfaces. They identify key challenges, such as the intrusive nature of sensing devices and the complexity of their deployment, alongside a general lack of technological readiness and heavy reliance on onsite support from researchers and technicians which may undermine sustainability. These practical challenges in the deployment and application of LA in authentic education settings underscore the need for close alignment between technological advancements and pedagogical intentions (i.e., connecting LA with learning design).

### Emergent design issues

In Table 1, we present a summary of the design issues emerging from our review of the literature. They underscore the complexities and challenges inherent in designing LA for formative assessment of group work, including challenges in identification and fostering of skills, assessment, data collection and analysis and creation of relevant and actionable feedback.

Table 1
*Summary of design issues identified in the literature*

| Area | Design issues |
|---|---|
| Identification and fostering of skills | 1. What challenges exist in identifying a comprehensive list of skills necessary for productive group work, and how can observable learner actions be used as proxy measures?<br>2. What strategies can be employed to foster collaboration literacy among students? |
| Assessment | 3. What complexities arise in formative assessment within collaborative learning environments, particularly concerning diverse interaction patterns and fluidity of roles?<br>4. How can we balance the need for individual accountability with the collaborative nature of group work in formative assessment design?<br>5. How can we develop strategies to overcome the existing limitations in assessing individual contributions within group work? |
| Data collection and analysis | 6. How can data collection on student contributions to group work be effectively utilised to enhance collaboration literacy? |

| | |
|---|---|
| Creation of relevant and actionable feedback | 7. How can we ensure that feedback provided in formative assessment is utilised by learners to enhance their performance at both the group and individual levels?<br>8. When integrating LA into formative assessment, what considerations should be made regarding who could benefit from the feedback and how it can be designed to be relevant and actionable for different stakeholders? |

The design issues identified provide an opportunity to work towards solutions in a structured manner and to conceptualise potential solutions, rather than being able to fully address these questions at this stage. Such potential solutions can inform experimental learning design, which can subsequently be tested.

### Learning design: Connecting collaboration, assessment and LA

The term *learning design* conceptualises both a teacher's cognitive act of planning a learning activity for their students (process) and documenting that pedagogical intent (product) in ways that could be reused and shared with others. Researchers have made connections between the fields of LA and learning design as an approach to understand and contextualise observed student behaviours connected to a learning activity (Lockyer & Dawson, 2011). This work has exemplified how these may be integrated conceptually (Bakharia et al., 2016) as well as through specific analytic approaches and design frameworks (Lockyer et al., 2013). Research and development in this field are concerned with understanding teachers' design practices as well as developing and testing approaches, frameworks, and tools to support teachers with both the design process and product (see, for example, S. Bennett et al., 2015; Laurillard, 2013). This paper considers the ACAD framework as a design framework that can be used to guide the process of designing formative assessment of collaborative group work using LA.

The ACAD framework (Goodyear & Carvalho, 2014) is concerned with designing learning opportunities by considering three key elements during design: set (tools and the digital and physical learning environment), social (roles and rules) and epistemic (the processes of knowledge building through tasks). Using an analogy of the theatre, Goodyear and Carvalho (2014) have argued that these three elements can be specifically designed. These elements, along with other features of the learning situation, will influence the activity of learners. When the purpose of formative assessment is considered, the ACAD framework highlights a fourth inseparable domain of co-configuration and co-construction of learning, when learners engage with, respond to, interpret and potentially modify that which has been designed. Importantly, the ACAD framework allows researchers (and learning designers) to identify the physical, epistemic and social dimensions of collaboration, and even affective dimensions (Echeverria et al., 2019; Goodyear et al., 2021). These dimensions can in turn inform the focus of the application of LA, in this case as related to formative assessment.

## A process to integrate LA and formative assessment of group work skills

To integrate LA with formative assessment and thus to enhance the evaluation of individual contributions in HE group work projects, we adopt an evidence-informed approach, building upon the insights of Alhadad and Thompson (2017), which employs the ACAD framework (Goodyear & Carvalho, 2014) alongside conjecture mapping (Sandoval, 2014). This combination aims to enhance assessment by providing a data-driven perspective on individual engagement and contributions through LA, tailored to the specific educational context and students.

Formative assessment principles guide this approach, focusing on continuous feedback to refine students' skills based on their individual contributions to the group. Integrating LA in formative assessment can provide vital, data-driven feedback to aid the improvement of individual performance and foster learning (Wise et al., 2023).

We identified five steps in this process, outlined in Table 2 and described below.

Table 2
*Process for integrating LA and formative assessment*

| Step | | Process elements | Design issue(s) |
|---|---|---|---|
| Step 1 | Identify and map skills for productive group work and observable (inter)actions | Learning design (ACAD)<br>Conjecture mapping | 1, 2 |
| Step 2 | Plan for strategic multimodal data collection | Multimodal data<br>LA | 6 |
| Step 3 | Initiate analytics frameworks: defining the analytical scope | LA | 3, 4 |
| Step 4 | Tailor feedback strategies | Feedback levels<br>LA | 7, 8 |
| Step 5 | Provide feedback to the design | Learning design | 5 |

### Step 1: Identify and map skills for productive group work and observable (inter)actions

Begin by defining a clear set of collaboration skills that align with the specific learning objectives of the group work project. These should be informed by educational theories and research to ensure they contribute to effective collaborative learning. Examples include conflict resolution and effective communication (Worsley, Anderson et al., 2021).

For each identified skill, develop design conjectures detailing how epistemic, set and social elements of the designed learning environment are expected to facilitate development of that skill. For example, if one of the skills is conflict resolution, a design conjecture might posit that tasks requiring negotiation of diverse perspectives will necessitate students to address and reconcile conflicting viewpoints.

Identify observable actions (individual contributions) that serve as proxy measures for each collaboration skill. These should be actions that can reasonably be expected to occur as a result of the learning environment elements hypothesised in the design conjectures. For example, observable actions for effective communication might include regularly contributing ideas in groups discussions and providing constructive feedback to peers. Individual contributions may include those made to discussions, management and problem-solving in relation to the *coordination of the group* (social); to the discussion, sensemaking and problem-solving in relation to the *task* in the form of discourse and text-based interactions (epistemic); and to the *collaboration product* in the form of shared documents and prototypes (set). This encompasses activity before, during and after the collaborative task, encapsulating preparation, productive participation and reflection, respectively.

Formulate theoretical conjectures linking observable actions to desired learning outcomes. This involves hypothesising how the manifestation of certain behaviours (resulting from the design of the learning environment) contribute to enhanced collaboration skills and, ultimately, improved learning outcomes. For instance, if students are regularly engaging in constructive feedback, the theoretical conjecture might suggest this leads to a deeper understanding of subject matter and improved interpersonal skills.

Visually map these relationships (from learning environment design, to activities, to outcomes). This conjecture map (see Table 3) can serve as a blueprint for subsequent steps in this process and the evaluation of the learning design. This process next involves identifying observable (inter)actions that may serve as proxy measures for collaboration skills and potential data sources through which they could be observed.

Table 3
*Mapping relations between the designed environment, intended outcomes and observations*

| Design features (ACAD) | Design conjectures | Theoretical conjectures | Outcomes | Observable (inter)actions | Multimodal observations |
|---|---|---|---|---|---|
| Set | Shared online documents to promote transparent, equitable and inclusive participation | Transparent documentation and continuous interaction with shared online documents foster democratic participation | Increased ownership and responsibility among group members<br><br>Balanced contribution | Students' access, edits, comments and contributions to shared documents | Log files, video and screen recordings of meetings showing members engaging with shared documents |
| Epistemic | Tasks are designed to require diverse knowledge | Diversity in contributions leads to deeper understand of problem and innovation | Enhanced solution quality | Knowledge from diverse range of disciplines presented in group discussions | Meeting recordings, shared documents |
| Social | Structured tasks promote equitable participation | Equitable participation enhances group cohesion and knowledge construction | Balanced contribution and improved group cohesion | Distribution of task contributions among group members | Contribution tracking, participation logs |

Finally, link the observable (inter)actions to formative assessment criteria. Ensure criteria are clear, measurable and directly tied to the skills and actions defined earlier. This linkage ensures assessments are aligned with educational objectives and the designed learning activities, providing a coherent framework to evaluate individual and group contributions.

### Step 2: Plan for strategic multimodal data collection

Planning for strategical multimodal data collection encompasses identifying relevant data sets, understanding the granularity of data needed and selecting appropriate methods and tools for data collection. Additionally, this involves addressing the challenges and considerations unique to different learning environments and managing logistical aspects of collecting this data.

To provide appropriate feedback to students regarding their collaboration literacy, access to data related to the *processes* of group work, *artefacts created* and *communication* undertaken is required. This entails prioritising identification of potential data sets that enable evaluation of various facets of group work, from collective collaboration to individual input. As underscored by Stahl et al. (2013), collaboration is multifaceted and steeped in complexity, spanning from discourse and gaze to cognition and nuanced social skills. Praharaj et al. (2018) emphasised the variability of collaboration indicators across contexts, which invariably impacts learning design.

The range of data to be gathered will focus on the students' individual activity within the context of collaborative group projects. Consideration should be given to the specific features and measures of interest from each data source, including whether the focus is on micro-level (e.g., non-verbal behaviours) and/or macro-level (e.g., help giving and seeking) aspects. These data should be directly relevant to the (inter)actions identified in step one.

Start by identifying automatically captured (passive) data sets pertinent to the learning environment and learners. This may include the creation of automated processes that could identify relevant artefacts of learning, such as logs from learning management systems, online discussions and shared online documents and configure them into an output, or by the students themselves, as evidence to be evaluated by the teacher. The value of employing multiple streams of data is emphasised by Giannakos et al. (2019) in relation to predicting skill acquisition. However, although diverse forms of data can be actively collected through a range of sensing devices, focusing on a smaller number of more manageable forms of data, such audio, video and online documents, is likely to be more feasible, particularly for initial phases. Martinez-Maldonado et al. (2023) noted that most MMLA solutions rely primarily on analysis of audio and video data.

Key questions to be considered with multiple streams of data include whether they can be synchronised so they can be analysed together (Ochoa et al., 2018; Worsley, 2018), the noise sources that each data stream may carry and how the signal-to-noise ratio can be enhanced (e.g., being able to tell who is speaking when analysing audio data) (Sharma et al., 2019).

Choices regarding data collection tend to "reflect peculiarities of instructional settings" (Sharma & Giannakos, 2020, p. 1465). Interaction between learners on formal collaborative environments is often mediated by digital devices, whereas in informal collaborative settings, interaction occurs primarily through verbal discourse and gesture (Sharma & Giannakos, 2020). Data collection should therefore be informed by the settings in which groups work, which may include face to face, online or a blended mode, and the ways in which they work, which may be synchronous, asynchronous or a combination of both.

Where groups are required to work in a set location, such as the classroom, data collection may be captured through video and audio recording devices configured for that environment. When working online, this data may be captured through videoconferencing recording functions. However, individual contributions also occur outside of group meetings, meaning data collection should extend beyond this to include asynchronous contributions such as input into shared online documents.

Effective planning for multimodal data collection raises several logistical challenges to ensure the efficacy and reliability of the data gathered. This is particularly important if groups are required to contribute actively to data collection, (e.g., in settings such as informal group meetings outside of classrooms). Establishing clear guidelines and providing support will help to ensure the data they collect is consistent, reliable, and relevant, particularly if group work extends over several weeks. Ensuring consistent, reliable, and relevant data collection from varied contexts requires organisation, clear communication, and access to appropriate technologies, particularly if participants are expected to manage part of the data gathering process themselves.

### Step 3: Initiate analytics frameworks: Defining the analytical scope

Digital tools offer expansive capabilities to map where interactions and contributions occur across physical and digital spaces, broadening the context in which contributions to group work are assessed (Wise et al., 2023). Advanced analytics and machine learning algorithms can process and blend large quantities, and different types of data, such as physical interactions and video and audio cues, to determine the quality of group work and to identify patterns and trends that may not be immediately apparent (Spikol et al., 2018).

To maintain relevance and accuracy, the implementation of these tools should be guided by well-defined parameters that align with the specific collaboration skills identified in Step 1. This involves clarifying the specific aspects of individual contributions to analyse, focusing on not only the quantity but also the quality of these contributions and how they integrate within the collective efforts of the group. Consideration should also be given to the timescale of analysis. The level of granularity – whether analysing moment-to-moment interactions, entire meetings or weekly contributions – should align with the initial skills and actions identified, ensuring it corresponds appropriately with the analytical scale chosen.

In selecting analytics tools, prioritise those that can dissect individual contributions while contextualising them within the group setting. Social network analysis is a useful approach for both analysing interaction patterns and visualising them on a network diagram. It can make visible active, inactive and isolated participants within a group and enables identification of the distinct roles adopted by group members (Saqr et al., 2020). Therefore, it offers the potential to visualise and monitor the health of group dynamics based on the quantity and relational aspects of interaction data.

However, selected tools should ideally be capable of handling the multiple data sources identified in Step 2 and analysing them on a consistent timescale to ensure compatibility and coherence in data analysis (Echeverria et al., 2019). Quantitative ethnography, which allows both epistemic and social networks to be analysed and visualised using epistemic network analysis, is an approach that has been used in the analysis of multimodal data in collaborative environments and shows great promise for collaboration analytics (Echeverria et al., 2019; Martinez-Maldonado et al., 2021).

### Step 4: Tailor feedback strategies

Feedback strategies should consider the level, format, frequency and audience for feedback, ensuring it is relevant and actionable. Four levels of feedback: task, process, self-regulation, and self level (Hattie & Timperley, 2007), their purposes in relation to group work contributions, and considerations are outlined in Table 4.

Table 4
*Feedback level, purpose and considerations for assessment design*

| Level | Purpose | Considerations |
|---|---|---|
| Task | To provide feedback on individual contributions to tasks, including comparison to others. | Does the feedback clarify how their individual contributions align with the group's objectives? |
| Process | To help students understand the impact of their actions on their learning and group dynamics. | Is the aim to deepen students' understanding or to guide them towards more effective collaboration processes? |
| Self-regulation | To help students monitor their own skills and contributions. | Does feedback encourage reflection and self-assessment? Does it promote self-regulation? |
| Self level | To provide personal feedback that enhances motivation and confidence. | Does feedback balance praise with suggestions for improvement? Does it motivate students to contribute meaningfully? |

For example, task-level feedback may benefit teachers by providing detailed, objective data on individual contributions to tasks. It may also assist students in evaluating each other's contributions, enabling informed peer evaluations. Ultimately, feedback for students should be aimed at enhancing their collaboration skills. Task and process feedback could be provided with self-regulation feedback to prompt students' reflection on their own contributions relative to others with the aim of enhancing their collaboration skills.

Through LA, feedback can be presented using visualisation tools (e.g., dashboards), alerts and notifications. These tools can tailor recommendations, making feedback more relevant and impactful. Feedback frequency should be tailored – whether it be in real time, weekly or other pre-determined intervals – ensuring it is provided when it is both relevant and actionable.

### Step 5: Provide feedback to the design

Recognising the potential divergence and convergence between intended learning outcomes and actual student activity is pivotal for designing LA in the formative assessment of group work. This awareness necessitates analytics tools to be adaptive and dynamic, capturing pre-determined metrics and emergent patterns in group dynamics. Effective tools should offer holistic insights, balancing individual contributions with collective outcomes, and facilitating real-time interventions. However, alignment needs to be ensured between LA technologies and learning design (Lockyer et al., 2013). Misalignment can lead to analytics-driven practices that may not support, or may even undermine, pedagogical objectives (Sharma & Giannakos, 2020).

Ongoing dialogue between educators, technologists and learners ensures the analytics feedback loop is not just a technical process, but a pedagogical one, and continuous refinement of the design of learning activities based on insights from analytics and feedback from users is crucial (Arthars et al., 2019). This iterative process serves two purposes: firstly, evaluating the efficacy of the learning design based on whether learners achieve the intended outcomes; and secondly, dynamically adjusting the design in response to insights from the learning environment, thus supporting students' skills development within group contexts.

## Conclusion

In this paper, we explored the growing importance of collaborative group work skills aligned with graduate attributes. Our focus was on the integration of formative assessment with LA technologies to enhance these skills, addressing the inherent complexities of group work in HE settings. Our guiding research question asked how LA could be used for the formative assessment of collaborative group work skills.

We identified several design issues central to the successful integration of formative assessment and LA in the context of group work and collaboration skills. These related to identifying and fostering essential collaboration skills, managing complexities of assessing individual contributions within group contexts, applying strategic data collection and analysis methods and creating relevant and actionable feedback. Each design issue underscored the multifaceted nature of collaborative learning, and the nuanced approach needed for analytics-enabled formative assessment.

Responding to these design issues and drawing on research that considers design for learning, conjecture mapping, assessment design, MMLA and feedback, we have outlined a structured process for developing formative assessment of group work skills in collaborative projects and HE contexts. The process, created with the aim of enhancing educational experiences through timely, relevant and actionable feedback, seeks to overcome complexities and challenges associated with group work assessments.

In conclusion, the integration of formative assessment and LA represents a way to address the complexities of collaborative group work in HE. Future research should seek to test and refine these processes, ensuring they are responsive to stakeholder needs and adaptable to an evolving educational landscape.

## Author contributions

**Natasha Arthars:** Conceptualisation, Methodology, Writing – original draft, Writing – review and editing; Supervision, Project Administration; **Kate Thompson:** Conceptualisation, Methodology, Writing – original draft, Writing – review and editing; **Henk Huijser:** Conceptualisation, Writing – original draft, Writing – review and editing; **Steven Kickbusch:** Conceptualisation, Writing – original draft, Writing – review and editing; **Samuel Cunningham:** Conceptualisation, Writing – original draft, Writing – review and editing; **Gavin Winter:** Writing – original draft, Writing – review and editing; **Roger Cook:** Conceptualisation, Writing – original draft; **Lori Lockyer:** Writing – original draft, Writing – review and editing.

## References


Afzaal, M., Nouri, J., Zia, A., Papapetrou, P., Fors, U., Wu, Y., Li, X., & Weegar, R. (2021). Explainable AI for data-driven feedback and intelligent action recommendations to support students self-regulation. *Frontiers in Artificial Intelligence*, *4*, Article 723447. https://doi.org/10.3389/frai.2021.723447

Alhadad, S. S. J., & Thompson, K. (2017). Understanding the mediating role of teacher inquiry when connecting learning analytics with design for learning. *Interaction Design and Architecture(s) Journal*, *33*, 54–74. https:/doi.org/10.55612/s-5002-033-003

Aljohani, N. R., & Davis, H. C. (2013). Learning analytics and formative assessment to provide immediate detailed feedback using a student centered mobile dashboard. In K. Al-Begain & R. Bestak (Eds.), *Proceedings of the 2013 Seventh International Conference on Next Generation Mobile Apps, Services and Technologies* (pp. 262–267). IEEE. https://doi.org/10.1109/NGMAST.2013.54

Arthars, N., Dollinger, M., Vigentini, L., Liu, D. Y. T., Kondo, E., & King, D. M. (2019). *Empowering teachers to personalize learning support.* In D. Ifenthaler, D. Mah, & J. Y. K. Yau (Eds.), Utilizing learning analytics to support study success (pp. 223–248). Springer. https://doi.org/10.1007/978-3-319-64792-0_13

Bakharia, A., Corrin, L., De Barba, P., Kennedy, G., Gašević, D., Mulder, R., Williams, D., Dawson, S., & Lockyer, L. (2016). A conceptual framework linking learning design with learning analytics. In D. Gašević & G. Lynch (Chairs), *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 329–338). Association for Computing Machinery. https://doi.org/10.1145/2883851.2883944

Balasooriya, C., Olupeliyawa, A., & Iqbal, M. P. (2016). Innovative assessment that combines collaborative and self-directed learning with integration and application of knowledge: Teamwork group projects. *MedEdPORTAL*, *12*, Article 10452. https://doi.org/10.15766/mep_2374-8265.10452

Bartimote, K., Pardo, A., & Reimann, P. (2018). The perspective realism brings to learning analytics in the classroom. In J. M. Lodge, J. Cooney Horvath, & L. Corrin (Eds.), *Learning analytics in the classroom* (pp. 22–42). Routledge.

Bennett, R. E. (2011). Formative assessment: A critical review. *Assessment in Education: Principles, Policy & Practice*, *18*(1), 5–25. https://doi.org/10.1080/0969594X.2010.513678

Bennett, S., Agostinho, S., & Lockyer, L. (2015). Technology tools to support learning design: Implications derived from an investigation of university teachers' design practices. *Computers & Education, 81*, 211–220. https://doi.org/10.1016/j.compedu.2014.10.016

Black, P., & Wiliam, D. (2009). Developing the theory of formative assessment. *Educational Assessment, Evaluation and Accountability*, *21*, 5–31. https://doi.org/10.1007/s11092-008-9068-5

Blikstein, P. (2013). Multimodal learning analytics. In D. Suthers, K. Verbert, E. Duval, & X. Ochoa (Eds.), *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 102–106). Association for Computing Machinery. https://doi.org/10.1145/2460296.2460316

Boud, D. (2009). How can practice reshape assessment? In G. Joughin (Ed.), *Assessment, learning and judgement in higher education* (pp. 1–15). Springer. https://doi.org/10.1007/978-1-4020-8905-3_3

Brandler, S., & Roman, C. P. (2015). *Group work: Skills and strategies for effective interventions* (3rd ed.). Routledge. https://doi.org/10.4324/9781315764115

Briscoe, C. (1994). Making the grade: Perspectives on a teacher's assessment practices. *Mid-Western Educational Researcher*, *7*(4), 14–25. https://scholarworks.bgsu.edu/mwer/vol7/iss4/4

Buckingham Shum, S., Echeverria, V., & Martinez-Maldonado, R. (2019). The multimodal matrix as a quantitative ethnography methodology. In B. Eagan, M. Misfeldt, & A. Siebert-Evenstone (Eds.), *Communications in computer and information science: Vol. 1112*. *Advances in quantitative ethnography* (pp. 26–40). Springer. https://doi.org/10.1007/978-3-030-33232-7_3

Carless, D., & Boud, D. (2018). The development of student feedback literacy: Enabling uptake of feedback. *Assessment & Evaluation in Higher Education, 43*(8), 1315–1325. https://doi.org/10.1080/02602938.2018.14633544

Crisp, G., & Oliver, B. (2019). Re-imagining graduate achievement and employability. In J. Higgs, G. Crisp, & W. Letts (Eds.), *Practice futures: Vol. 2*. *Education for employability* (Vol. 1, pp. 73–82). Brill. https://doi.org/10.1163/9789004400832_006

Davies, W. M. (2009). Groupwork as a form of assessment: Common problems and recommended solutions. *Higher Education*, *58*, 563–584. https://doi.org/10.1007/s10734-009-9216-y
Echeverria, V., Martinez-Maldonado, R., & Buckingham Shum, S. (2019). Towards collaboration translucence: Giving meaning to multimodal group data. In S. Brewster & G. Fitzpatrick (Chairs), *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Paper No. 39, pp. 1–16). Association for Computing Machinery. https://doi.org/10.1145/3290605.3300269
Echeverria, V., Martinez-Maldonado, R., Yan, L., Zhao, L., Fernandez-Nieto, G., Gašević, D., & Shum, S. B. (2022). HuCETA: A framework for human-centered embodied teamwork analytics. *IEEE Pervasive Computing*, *22*(1), 39–49. https://doi.org/10.1109/MPRV.2022.3217454
Fallows, S., & Chandramohan, B. (2001). Multiple approaches to assessment: Reflections on use of tutor, peer and self-assessment. *Teaching in Higher Education*, *6*(2), 229–246. https://doi.org/10.1080/13562510120045212
Forsell, J., Forslund Frykedal, K., & Chiriac, E. H. (2021). Teachers' perceived challenges in group work assessment. *Cogent Education*, *8*(1), Article 1886474. https://doi.org/10.1080/2331186X.2021.1886474
Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, *28*, 68–84. https://doi.org/10.1016/j.iheduc.2015.10.002
Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59*, 64–71. https://doi.org/10,1007/s11528-014-0822-x
Giannakos, M. N., Sharma, K., Pappas, I. O., Kostakos, V., & Velloso, E. (2019). Multimodal data as a means to understand the learning experience. *International Journal of Information Management*, *48*, 108–119. https://doi.org/10.1016/j.ijinfomgt.2019.02.003
Goodyear, P., & Carvalho, L. (2014). Framing the analysis of learning network architectures. In L. Carvalho & P. Goodyear (Eds.), *The architecture of productive learning networks* (1st ed., pp. 48–70). Routledge.
Goodyear, P., Carvalho, L., & Yeoman, P. (2021). Activity-Centred Analysis and Design (ACAD): Core purposes, distinctive qualities and current developments. *Educational Technology Research and Development*, *69*, 445–464. https://doi.org/10.1007/s11423-020-09926-7
Goodyear, P., Jones, C., & Thompson, K. (2014). Computer-supported collaborative learning: Instructional approaches, group processes and educational designs. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), *Handbook of research on educational communications and technology* (pp. 439–452). Springer. https://doi.org/10.1007/978-1-4614-3185-5_35
Hamer, L. O., & O'Keefe, R. D. (2013). Achieving change in student's attitudes toward group projects by teaching group skills. *Journal of Higher Education Theory and Practice, 13*(2), 25–33.
Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research, 77*(1), 81–112. https://doi.org/10.3102/003465430298487
Howard, S., Thompson, K., & Pardo, A. (2018). Opening the black box: Developing methods to see learning in contemporary learning environments. In J. M. Lodge, J. Cooney Horvath, & L. Corrin (Eds.), *Learning analytics in the classroom* (pp. 152–164). Routledge. https://doi.org/10.4324/9781351113038-10
Hu, X., Ng, J. T., & Chu, S. K. (2022). Implementing learning analytics in wiki-supported collaborative learning in secondary education: A framework-motivated empirical study. *International Journal of Computer-Supported Collaborative Learning*, *17*(3), 427–455. https://doi.org/10.1007/s11412-022-09377-7
Ibarra-Sáiz, M. S., Rodríguez-Gómez, G., & Boud, D. (2020). Developing student competence through peer assessment: The role of feedback, self-regulation and evaluative judgement. *Higher Education*, *80*, 137–156. https://doi.org/10.1007/s10734-019-00469-2
Jones, A. (2009). Generic attributes as espoused theory: The importance of context. *Higher Education*, *58*, 175–191. https://doi.org/10.1007/s10734-008-9189-2
Kaliisa, R., Rienties, B., Mørch, A. I., & Kluge, A. (2022). Social learning analytics in computer-supported collaborative learning environments: A systematic review of empirical studies. *Computers and Education Open*, *3*, Article 100073. https://doi.org/10.1016/j.caeo.2022.100073

Laurillard, D. (2013). *Teaching as a design science: Building pedagogical patterns for learning and technology*. Routledge. https://doi.org/10.4324/9780203125083

Li, H., Xiong, Y., Hunter, C. V., Guo, X., & Tywoniw, R. (2020). Does peer assessment promote student learning? A meta-analysis. *Assessment & Evaluation in Higher Education*, *45*(2), 193–211. https://doi.org/10.1080/02602938.2019.1620679

Lockyer, L., & Dawson, S. (2011). Learning designs and learning analytics. *Proceedings of the 1st international conference on learning analytics and knowledge* (pp. 153–156). In P. Long & G. Siemens (Chairs), *Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 153–156). Association for Computing Machinery. https://doi.org/10.1145/2090116.2090140

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist, 57*(10), 1439–1459. https://doi.org/10.1177/0002764213479367

Maki, P. L. (2023). *Assessing for learning: Building a sustainable commitment across the institution* (2nd ed.). Routledge. https://doi.org/10.4324/9781003443056

Martinez-Maldonado, R., Echeverria, V., Fernandez-Nieto, G., Yan, L., Zhao, L., Alfredo, R., Li, X., Dix, S., Jaggard, H., Wotherspoon, R., Osborne, A., Shum, S. B., & Gašević, D. (2023). Lessons learnt from a multimodal learning analytics deployment in-the-wild. *ACM Transactions on Computer-Human Interaction*, *31*(1), 1–41. https://doi.org/10.1145/3622784

Martinez-Maldonado, R., Echeverria, V., Santos, O. C., Santos, A. D. P. D., & Yacef, K. (2018). Physical learning analytics: A multimodal perspective. In A. Pardo, K. Bartimote-Aufflick, & G. Lynch (Chairs), *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 375-379). Association for Computing Machinery. https://doi.org/10.1145/3170358.3170379

Martinez-Maldonado, R., Gaševic, D., Echeverria, V., Fernandez Nieto, G., Swiecki, Z., & Buckingham Shum, S. (2021). What do you mean by collaboration analytics? A conceptual model. *Journal of Learning Analytics, 8*(1), 126–153. https://doi.org/10.18608/jla.2021.7227

McCallum, S., & Milner, M. M. (2021). The effectiveness of formative assessment: Student views and staff reflections. *Assessment & Evaluation in Higher Education, 46*(1), 1–16. https://doi.org/10.1080/02602938.2020.1754761

McConnell, D. (2005). Examining the dynamics of networked e-learning groups and communities. *Studies in Higher Education, 30*(1), 25–42. https://doi.org/10.1080/0307507052000307777

McMillan, J. H. (2014). *Classroom assessment: Principles and practice for effective standard-based instruction.* Pearson.

Michaelsen, L. K. & Sweet, M. (2008). The essential elements of team-based learning. *New Directions for Teaching and Learning*, 116, 7–27. https://doi.org/10.1002/tl.330

Ochoa, X., Domínguez, F., Guamán, B., Maya, R., Falcones, G., & Castells, J. (2018, March). The RAP system: Automatic feedback of oral presentation skills using multimodal analysis and low-cost sensors. In A. Pardo, K. Bartimote-Aufflick, & G. Lynch (Chairs), *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 360–364). Association for Computing Machinery. https://doi.org/10.1145/3170358.3170406

Oliver, B., & Jorre de St Jorre, T. (2018). Graduate attributes for 2020 and beyond: Recommendations for Australian higher education providers. *Higher Education Research & Development*, *37*(4), 821–836. https://doi.org/10.1080/07294360.2018.1446415

Oviatt, S., & Cohen, A. (2014). Written activity, representations and fluency as predictors of domain expertise in mathematics. In A. Ali Salah, J. Cohn, & B. Schuller (Chairs), *Proceedings of the 16th International Conference on Multimodal Interaction* (pp. 10-17). Association for Computing Machinery. https://doi.org/10.1145/2663204.2663245

Praharaj, S., Scheffel, M., Drachsler, H., & Specht, M. (2018). Multimodal analytics for real-time feedback in co-located collaboration. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Draschler, R. Elferink, & M. Scheffel (Eds.), Lecture notes in computer science: Vol. 11082. *Lifelong technology-enhanced learning* (pp. 187–201). Springer. https://doi.org/10.1007/978-3-319-98572-5_15

Qureshi, M. A., Khaskheli, A., Qureshi, J. A., Raza, S. A., & Yousufi, S. Q. (2023). Factors affecting students' learning performance through collaborative learning and engagement. *Interactive Learning Environments*, *31*(4), 2371–2391. https://doi.org/10.1080/10494820.2021.1884886

Raković, M., Gašević, D., Hassan, S. U., Ruipérez Valiente, J. A., Aljohani, N., & Milligan, S. (2023). Learning analytics and assessment: Emerging research trends, promises and future opportunities. *British Journal of Educational Technology, 54*(1), 10–18. https://doi.org/10.1111/bjet.13301
Rasul, T., Nair, S., Kalendra, D., Robin, M., de Oliveira Santini, F., Ladeira, W. J., Sun, M., Day, I., Rather, R. A., & Heathcote, L. (2023). The role of ChatGPT in higher education: Benefits, challenges, and future research directions. *Journal of Applied Learning and Teaching*, *6*(1), 41–56. https://doi.org/10.37074/jalt.2023.6.1.29
Reimann, P., Frerejean, J., & Thompson, K. (2009). Using process mining to identify models of group decision making processes in chat data. In C. O'Malley, D. Suthers, P. Reimann, & A. Dimitracopoulou (Eds), *Proceedings of the 2009 Computer-supported Collaborative Learning Practices Conference* (pp. 98–107). International Society of the Learning Sciences. https://repository.isls.org/handle/1/3020
Sandoval, W. (2014). Conjecture mapping: An approach to systematic educational design research. *Journal of the Learning Sciences*, *23*(1), 18–36. https://doi.org/10.1080/10508406.2013.778204
Saqr, M., Nouri, J., Vartiainen, H., & Malmberg, J. (2020). What makes an online problem-based group successful? A learning analytics study using social network analysis. *BMC Medical Education, 20*, Article 80. https://doi.org/10.1186/s12909-020-01997-7
Schneider, B., Dowell, N., & Thompson, K. (2021). Collaboration analytics — Current state and potential futures. *Journal of Learning Analytics, 8*(1), 1–12. https://doi.org/10.18608/jla.2021.7447
Sharma, K., & Giannakos, M. (2020). Multimodal data capabilities for learning: What can multimodal data tell us about learning? *British Journal of Educational Technology*, *51*(5), 1450–1484. https://doi.org/10.1111/bjet.12993
Sharma, K., Papamitsiou, Z., & Giannakos, M. (2019). Building pipelines for educational data using AI and multimodal analytics: A "grey-box" approach. *British Journal of Educational Technology*, *50*(6), 3004–3031. https://doi.org/10.1111/bjet.12854
Shin, Y., Kim, D., & Song, D. (2020). Types and timing of scaffolding to promote meaningful peer interaction and increase learning performance in computer-supported collaborative learning environments. *Journal of Educational Computing Research*, *58*(3), 640–661. https://doi.org/10.1177/0735633119877134
Siemens, G., Long, P., Gašević, D., & Conole, G. (2011). *Call for papers, 1st International Conference Learning Analytics & Knowledge (LAK 2011)*. http://www.wikicfp.com/cfp/servlet/event.showcfp?eventid=11606
Spikol, D., Ruffaldi, E., Dabisias, G., & Cukurova, M. (2018). Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. *Journal of Computer Assisted Learning, 34*(4), 366–377. https://doi.org/10.1111/jcal.12263
Sprague, M., Wilson, K. F., & McKenzie, K. S. (2019). Evaluating the quality of peer and self evaluations as measures of student contributions to group projects. *Higher Education Research & Development, 38*(5), 1061–1074. https://doi.org/10.1080/07294360.2019.1615417
Stahl, G. (2010). Guiding group cognition in CSCL. *Computer Supported Learning, 5*, 255–258. https://doi.org/10.1007/s11412-010-9091-7
Stahl, G., Law, N., & Hesse, F. (2013). Reigniting CSCL flash themes. *International Journal of Computer-Supported Collaborative Learning, 8*, 369–374. https://doi.org/10.1007/s11412-013-9185-0
Strijbos, J. W., & De Laat, M. F. (2010). Developing the role concept for computer-supported collaborative learning: An explorative synthesis. *Computers in Human Behavior, 26*(4), 495–505. https://doi.org/10.1016/j.chb.2009.08.014
Sun, Z., & Theussen, A. (2023). Assessing negotiation skill and its development in an online collaborative simulation game: A social network analysis study. *British Journal of Educational Technology*, *54*(1), 222–246. https://doi.org/10.1111/bjet.13263
Thompson, K., Ashe, D., Carvalho, L., Goodyear, P., Kelly, N., & Parisio, M. (2013). Processing and visualizing data in complex learning environments. *American Behavioral Scientist, 57*(10), 1401–1420. https://doi.org/10.1177/0002764213479368
Thompson, K., Corrin, L., & Lodge, J. M. (2023). AI in tertiary education: Progress on research and practice. *Australasian Journal of Educational Technology, 39*(5), 1–7. https://doi.org/10.14742/ajet.9251

Weaver, D., & Esposto, A. (2012). Peer assessment as a method of improving student engagement. *Assessment & Evaluation in Higher Education, 37*(7), 805–816. https://doi.org/10.1080/02602938.2011.576309

Wise, A. F., Rosé, C., & Järvelä, S. (2023). Nine elements for robust collaborative learning analytics: A constructive collaborative critique. *International Journal of Computer-Supported Collaborative Learning, 18*, 1–9. https://doi.org/10.1007/s11412-023-09389-x

Wong, A., & Chong, S. (2018). Modelling adult learners' online engagement behaviour: proxy measures and its application. *Journal of Computers in Education, 5*, 463–479. https://doi.org/10.1007/s40692-018-0123-z

Worsley, M. (2018). Multimodal learning analytics' past, present, and potential futures. In R. Martinez-Maldonado, V. Echeverria, L. P. Prieto, M. J. Rodriguez-Triana, D. Spikol, M. Curukova, M. Mavrikis, X. Ochoa, M. Worsley (Eds.), *Proceedings of the Second Multimodal Learning Analytics Across (Physical and Digital) Spaces* (Vol. 2163, pp. 1–16). CEUR. https://ceur-ws.org/Vol-2163/paper5.pdf

Worsley, M., Anderson, K., Melo, N., & Jang, J. (2021). Designing analytics for collaboration literacy and student empowerment. *Journal of Learning Analytics*, *8*(1), 30–48. https://doi.org/10.18608/jla.2021.7242

Worsley, M., Martinez-Maldonado, R., & D'Angelo, C. (2021). A new era in multimodal learning analytics: Twelve core commitments to ground and grow MMLA. *Journal of Learning Analytics*, *8*(3), 10–27. https://doi.org/10.18608/jla.2021.7361

Worsley, M., & Ochoa, X. (2020). Towards collaboration literacy development through multimodal learning analytics. In M. Giannakos, D. Spikol, I. Molenaar, D. Di Mitri, K. Sharma, X. Ochoa, & R. Hammad (Eds.), *Proceedings of CrossMMLA in Practice: Collecting, Annotating and Analyzing Multimodal Data Across Spaces* (Vol. 2610, pp. 53–63). CEUR. http://ceur-ws.org/Vol-2610/

---

**Corresponding author**: Natasha Arthars, natasha.arthars@qut.edu.au



**Please cite as**: Arthars, N., Thompson, K., Huijser, H., Kickbusch, S., Cunningham, S., Winter, G., Cook, R., & Lockyer, L. (2024). Formative assessment of group work skills: An analytics-enabled conceptual framework. *Australasian Journal of Educational Technology*, *40*(4), 138–153. https://doi.org/10.14742/ajet.9444