# Supporting Knowledge Building with Analytics and Augmented Intelligence – Building on the Emerging Works

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**Abstract:** Knowledge building pedagogy requires teachers to be adaptive and apply appropriate principles in guiding students' emergent idea improvement. While there are emerging works on the use of analytics to support knowledge building, this area of work is still under-developed. This paper presents a review of the current state of work on the use of learning analytics with knowledge building data and multimodal data and identifies areas where artificial intelligence (AI) could be harnessed to provide adaptive support. A set of guiding questions that can be used to guide research and development in this area is also proposed.

## Introduction

Knowledge Building research (Scardamalia & Bereiter, 2015), is one of the most enduring and prominent research themes in the learning sciences (Chen & Hong, 2016). It remains relevant as it aims to tackle one of the most intractable problems in this Knowledge Age: developing knowledge building capacity of people. One distinct characteristic of this line of research is that the advancement in the supportive technologies, Knowledge Forum®, as well as related technologies such as promising ideas tool, were developed in tandem with the progress made in theories. Knowledge building research has taken a design implementation approach, which constantly tests and refines the design principles to tackle authentic classroom challenges. This paper discusses how to leverage advances in analytics and artificial intelligence (AI) to augment knowledge building processes.

Designing and facilitating knowledge building can be challenging as it differs from the predominant instructional practices that have prescriptive procedures to follow. To design for knowledge building lessons, a teacher needs to adopt a principle-based approach (Zhang et al., 2011), and follow students' collective idea development closely. Besides, it also advocates an embedded assessment that requires one to examine students' knowledge artifacts as evidence of their knowledge advancement, rather than using the predominant testing-after-learning assessment regime. All these calls for adaptive classroom practices (Männikkö & Husu, 2019) that require constant decision making as the students engage in collaborative idea improvement. To address these challenges, teachers and students need relevant information for their decision making. In terms of technological support, current computer-supported collaborative learning technologies focus on "static forms of support, such as structured interfaces, prompts, and assignment of students to scripted roles" (Rosé & Ferschke, 2016, p. 663), no doubt there is emerging research that aims to develop analytical tools or the external processing of learning analytics to work on the KF data. Building on the advancement in technologies and data science, this paper proposes how the power of AI could be harnessed to provide learning support. The intention is not to use AI to replace human intelligence in guiding knowledge building work; doing so will be running against the very purpose of developing students' capacity in knowledge work. Rather, the focus is on how students and teachers could work in intellectual partnership with computers that generate timely insights from data, to engage in knowledge building more efficiently and effectively. Thus the choice of the term augmented intelligence, and not AI, in the title of this paper.

For clarity, we start with a short explanation of analytics and AI for education. Analytics, in essence, refers to the systematic applications of quantitative methods (including statistics) to enhance decision making (Davenport & Harris, 2017), especially in situations when there are a massive amount of data to make sense of. Analytics can be *descriptive*, which is based on data from past events, or *predictive*, which projects into future possibilities (Reavie, 2018). While some experts (e.g., Reavie, 2018) opined that AI can make assumptions and learn autonomously but analytics does not, others view AI as a continuum from analytics. For example, Davenport (2018) labelled AI as Analytics 4.0.

AI refers to studies and applications of how machines perceive and process information from the environment and take actions towards achieving a goal, thus simulating the abilities of cognitive thinking and exhibiting adaptive behaviors, just like human beings (Hinojo-Lucena et al., 2019). Developed since the 1950s, the resurgence of interest in AI in the 21st century can be attributed to the advancement in computing power and ability to process big data, which enables translation into many practical applications, such as image recognition and auto-text correction. AI often involves machine learning, which primarily focuses on the study of computer algorithms that can automatically improve through experience (Mitchell, 1997). Deep Learning is a machine learning technique that seeks to define neural networks based on pattern recognition from input data (Contreras & De La Rosa, 2016). The "deep" in Deep Learning refers to the multiple transformation layers and levels of representation that lie between the neural network inputs and outputs (Hernández-Blanco et al.,2019).

There are some emergent works on the use of analytics for knowledge building, but it is still an under-researched area.

## A review of analytics/AI for knowledge building framework

A search was conducted via the authors' library system that integrates over 50 databases. The search terms "knowledge building" or "knowledge creation" AND "analytics or big data or artificial intelligence" AND "education or school or learning or teaching or classroom or education system" were entered. There were 90 articles identified and 18 articles were shortlisted after going through the abstracts. After reading the articles, only 9 were found to be relevant to knowledge building (Scardamalia & Bereiter, 2015). This small number is not surprising given that research on the use of analytics and AI for knowledge building is in its infancy stage. For parsimony, we only included one article on the same product or approach. To analyze the current work, the following questions were asked: (1) which aspect(s) of knowledge building is/are supported?; (2) what are the related knowledge building principles? (3) what kinds of analytics or AI techniques are used?; (4) What are the main outcomes of the studies? Table 1 summarizes the relevant information among the studies presented in these 9 papers that involved analytics or the use of machine learning.

Among these 9 articles, most of the studies focus on socio-cognitive aspects of knowledge building and the associated principles related to knowledge building discourse and idea improvement. Also, visualization of analytics tools was used by students in three studies (Chen & Zhang, 2016; Hong et al., 2015; Resendes et al., 2015), often as students' choice rather than teacher's instruction or scripted activities. For the other studies, analytics or machine learning are used by researchers as research tools. There is only one study (Zhu et al., 2019) that investigated students' emotions associated with knowledge building. Concerning the types of analytics or AI technologies employed, a combination of a range of technologies was used: KF analytics tools (Hong et al., 2015; Resendes et al., 2015), text mining and topic modelling (Chen et al., 2015; Chen, Zhang, & Lee, 2013; Lee & Tan, 2017), temporal analysis (Chen et al., 2017; Lee & Tan, 2017), latent semantic analysis and frequent sequence mining (Chen et al., 2017), KBDex analytics followed by betweenness-centrality trends and degree-centrality/betweenness-centrality graph with clustering (Lee & Tan, 2017), speech emotion analysis, prosody, sentiment analysis, content analysis of multimodal data (Zhu, Xing, Costa, Scardamalia, & Pei, 2019), and sequential patterns analysis (Zhu et al, 2019).

How do we make sense of these emerging works and more critically, how and where do we go from here? One apparent and expected similarity among these studies is the central role of the guiding principles of knowledge building. Another observation is that the study on the emotional aspect of knowledge building is only featured in one study, although we can argue that such a study, in general, is also lacking in knowledge building research. Nevertheless, the advancement in technologies and analytics present opportunities to explore the emotional aspects of knowledge building. For example, natural language processing and sentiment analysis could be employed to study texts written by students. Advancement in the internet of things such as wearable devices could also be explored to provide a constant stream of physiological data (e.g., heartbeat), which afford moment-to-moment analyses of emotions that are not feasible in the traditional methods of self-report and use of psychological instruments. One less apparent observation is that the analytics could be designed for the students ultimately, but in many studies, used by the researchers.

Table 1. Research on the use of analytics and AI to support knowledge building

| Authors | Cognitive-social-emotional | Related KB principles | Analytics/AI | Outcomes |
|---|---|---|---|---|
| Oshima, Oshima, & Matsuzawa (2012) | Socio-cognitive | KB discourse | Text mining<br>KBDeX: social network analysis (of notes and ideas in the notes) | KBDeX analysis provides an alternative assessment for discourse advancement in knowledge building. |
| Chen, Resendes, Scardamalia, & Chuy (2012) | Socio-cognitive<br>• Promising ideas | KB discourse<br>Real ideas; idea improvement; diversity of ideas; Rise above | Topic modelling:<br>• Latent semantic analysis – compare students' ideas with authoritative sources | Students can make promisingness judgement; scientific level and domain knowledge improved. |
| Hong, Scardamalia, Messina, &Teo (2015). | Socio-cognitive<br>• Vocabulary growth;<br>• vocabulary overlap with curriculum<br>• Social network | All; principle-based design | • Use of analytics as knowledge building tools<br>• Vocabulary<br>• Analyzer, a Social Network Tool, and a Semantic Overlap Tool. | Increase in use of key terms; shift from problem generation to self-assessment; analytics tools help students to be more self-directed |
| Resendes, Scardamalia, Bereiter, & Chen (2015) | Meta-cognitive-social | KB discourse | • Word clouds<br>• Epistemic Discourse Moves tool<br>• KBDeX: degree centrality (DC), betweenness centrality (BC) and closeness centrality (CC). | Grade 2 children can engage in metadiscursive reflection and their vocabulary development. Feedback tools useful for children to address group cognition. |
| Chen & Zhang (2016) | Socio-cognitive<br>Promising ideas | • Epistemic agency<br>• KB discourse<br>• Idea centric principles | • Text analysis to merge promising ideas and calculate similarities among promising ideas<br>• Epistemic Discourse Moves tool<br>• Temporal analytics<br>• Automatic text analysis and topic modelling | Framework for KB analytics. Characteristics of KB analytics: agency-driven, choice-based, and progress oriented. |
| Lee & Tan (2017) | Cognitive<br>Promising ideas | Idea improvement; diversity of ideas | • Text mining<br>• Temporal analytics<br>• Cluster analysis<br>• KBDeX: degree centrality (DC), betweenness centrality (BC) graph over time, DC-BC graph | Temporal analytics and machine learning can help to identify promising ideas |
| Chen, Zhang, & Lee (2013) | Socio-cognitive<br>Meta knowledge building structure | KB meta-discourse, idea improvement and rise above | • Multilevel analysis and visualization of threads of ideas | Visualization of Idea-threads helps students to engage in meta-discourse and rise above of ideas. |
| Chen, Resendes, Chai, & Hong (2017) | Socio-cognitive<br>Discourse move | KB discourse | • Temporal analytics<br>• Lag-sequential Analysis (LsA)<br>• Frequent Sequence Mining (FSM) | Identification of patterns and sequence of discourse moves among more productive KB threads |
| Zhu, Xing, Costa, Scardamalia, & Pei (2019) | Cognitive-Emotions | Emotions and idea improvement | • Speech emotion analysis (prosodic analysis)<br>• Sentiment analysis from text | Identification of types of emotions that co-occur with different level of idea improvement |

## Guiding questions for augmenting knowledge building with analytics or AI

To guide future development of intelligent collaborative learning supports, Rummel, Walker and Aleven (2016) proposed that researchers could consider educational theory and multiple factors – the timing of support, psychological realms of support (cognitive, social, metacognitive, affective), mode of support (implicit or explicit), locus of support (direct or indirect), and target of support (group formation, peer support, domain support or social skills). Building on Rummel et al. (2016) recommendations and considering agenda of knowledge building research, we propose two sets of guiding questions, starting with the focus of knowledge building, then the nature and types of analytics or AI to augment knowledge building. Moving forward, developing a set of guiding questions for the use of analytics or AI to augment knowledge building could be useful. One approach is to envision what kinds of questions the researchers of the above-reviewed studies might ask. It is important to take this set of questions in totality for holistic considerations.

1a. What challenges are we addressing? Which principles of knowledge building is/are the focus?

As in most design-implementation research, challenges encountered in the design and/or implementation often provides the impetus for change innovation. The challenges can be multi-dimensional: ranging from technical developmental challenge, methodological challenge, and practical challenges. Given that design of knowledge building takes a principle-based approach (Zhang et al., 2011), identify the specific principle(s) is a critical consideration, which is apparent in the studies reviewed. For instance, the issue of identifying promising ideas motivated several studies (Che et al., 2012; Chen & Zhang, 2016; Lee & Tan, 2017) and is related to the idea-centric principles of knowledge building.

1b. Which aspects of knowledge building is augmented (e.g., Social, cognitive, metacognitive, emotional)?

Identifying the aspects of knowledge building or what Rummel et al. (2016) refer to as the psychological realms (cognitive, social, metacognitive and affective) could be useful as it has implications on the source of data (see Question 2 below) as well as the outcomes. For example, students' notes (text) could be a logical source for the cognitive and metacognitive aspects of knowledge building, and their interaction patterns the source of social aspects of knowledge building. That said, socio-cognitive interactions are also analyzed as in the case of KBDex (Oshima et al., 2012). This question to determine specific aspects of KB as we work with the huge potential of AI is especially important to avoid two extremes: to avoid narrowing the measure of these critical learning processes into a "score", and to avoid getting into a web of data that does not make much sense to the practitioner.

1c. How does this augmentation enable the advancement of knowledge building beyond the current methods (e.g., supporting idea advancement)?

This question is critical because we need to be cognizant that some of the goals and practices of analytics or AI in the field may not be compatible with the guiding principles of knowledge building. For example, the use of conversational agents that emulate good tutor's dialogue (e.g., Evens & Michael, 2006) may not be appropriate for knowledge building because it might position the "e-tutor" as the mediator of the conversation among students, and discourage peer-to-peer interaction – a situation we want to avoid in knowledge building. On the other hand, research on using machine learning to perform auto-segmenting of discourse (Mu et al., 2012) and automatic text tagging (Rosé et al., 2008) could be applied to knowledge building discourse move and extend the study by Chuy et al. (2011). If a machine can automatically perform segmenting of discourse and detect discourse moves, then automatic adaptive support can be developed to facilitate or encourage productive students' interactions (Walker, Rummel, & Koedinger, 2011); for instance, reflective prompts could appear to ask students to reflect on their discourse move or student-activated resources or hints about their progress of knowledge building could be provided.

2a. Which types of data are involved? (e.g., text, social interactions, cognitive interactions, voice, video, multimodal)? How do we integrate the various sources of data?

The availability, quantity, and quality of data forms the foundation for analytics and AI. Knowing which data are involved helps in the planning of data capturing, mining, cleaning and processing. For example, in natural language processing, the choice of stop words could be complex and requires a nuanced understanding of what is being analyzed. The term "please" could be a stop word in most cases, but could be important in sentiment analysis. Another less explored research in knowledge building is to study the process across both online and face-to-face settings. This necessitates the integration of different modalities of data (text in the forum, voices in the classrooms), yet pursuing the same focus of analysis. This component of data-types, though normally relate to research, can create positive shifts in a usually uni-dimensional traditional classroom practice. The use of multimodal-data in the classroom can make teachers and students aware of new modes of interaction.

2b. Which levels and types of analysis are involved? (e.g., unit of analysis, level of analysis, temporal analysis)?

The study by Chen and Zhang (2016) illustrated how these questions guide their choice of analytics. Based on the design principles of knowledge building (epistemic agency and design mode of thinking), they proposed a choice-based, progress-oriented, multi-level, multi-unit, and multi-timescale analytics and illustrated the analytics with three case examples. In essence, choice-based analytics is to support epistemic agency of learners by empowering them with the choices of viewing and making use of analytics to advance their knowledge building practices, specifically, choices of working on emergent ideas, of pursuing themes of inquiry and higher-order conceptual structures, and discourse move. The analytics is progress-oriented because of the focused goals of improving the breadth and depth of ideas and the emergence of new strands of inquiry. It can involve multi-unit (e.g., analyzing individuals to a community), multi-level (e.g., relating ideas within a thread to across threads) and multi-timescale (e.g., temporal analysis of idea across time). Indeed, while the data from each student allow us to track their progress individually, the principle of collective cognitive responsibility to contribute to the advancement of collective knowledge means that group-level analyses are necessary. For the previous question, we discussed the integration of data across modalities. Within each modality, there is also a need to analyze data across levels. This is illustrated in Zhang and Chen's (2019) work on idea-thread analysis, where ideas across different threads are tracked to provide a holistic and coherent visualization of how ideas develop within a community.

There is a growing interest in temporal analytics (Knight, Wise, Chen, & Cheng, 2015) as it can help to trace interactions or development of ideas against time to gain deeper insights into what is going on within a discourse. Reimann (2009) argued that temporal analysis is important because the traditional notion of "independent measures" may not be immutable throughout a discourse supported by CSCL. By examining the entire discourse and focusing on certain features, the temporal details collected at the micro-level across time can be examined with the underlying theory operating at a macro level (Mercer, 2008). In addition to the KBDeX (Oshima et al., 2012), there are other methods and tools (e.g., SNAPP; Bakharia & Dawson, 2011) that can work as near real-time interaction diagnostic tool for social network analysis.

2c. What is the nature of the analytics / AI? (e.g., descriptive, diagnostic, predictive, prescriptive, reflective) How are the results of the analytics / AI presented?

Currently, the suite of built-in analytics in Knowledge Forum provides descriptive information as the foundation (e.g., online activity across time). But it is also critical to consider how such information can be used. For example, if the use of scaffolds by students is coupled with reflective activities with the students (Hong et al., 2015), the analytics can serve the reflective function. The information on social network analysis can be diagnostic, in the sense of diagnosing whether there are students who are disengaged, or there are cliques within a class. The study by Lee and Tan (2017), to some extent, predicts which ideas are promising, based on the trend of betweenness centrality values of notes up to the time of analysis. Thus, it is not simply the consideration of how the results are presented, but how they are used. The prescriptive function is less compatible with knowledge building principles since the student's agency is prized.

2d. Who is the target audience of the results (students, teachers, researchers)?

The clarification of who the target audience could reflect the phase of the exploration of analytics. The ultimate goal, as what Chen and Zhang (2016) proposed, is to encourage student agency, thus having students as the target audience. Teachers, however, could use the analytics as information to provide scaffold or guidance to the students. Researchers' use of analytics usually reflects that the use of analytics is still being investigated.

What has not been explored is the adaptive intelligent support that initiates actions based on diagnostic outcomes. For instance, if the system detects that certain scaffolds have not been used after some time (and the normal model shows that students could have proceeded to rise above), there could be reflective prompts appearing for students to think about moving into another phase of idea building.

## A pilot with multilevel multimodal data

As an illustration, we describe how the above questions were used to guide a recent experiment called *Student Design Studio* in which 37 students, aged 10-16, from 7 schools in Singapore, were brought together to tackle the real-world challenge of sustainable living. Working through the set of questions help us to decide on the data collection and the nature of analytics to consider.

1. Which principles of knowledge building is/are the focus?
   - Real ideas, authentic problem: Engaging students with a real-world problem for sustainable verticle farming in Singapore. With this as design principles, it is then our goal to get the analytics to provide indicators about how real or how authentic the students' ideas are. Questions such as "how close are they getting to understand the problem that actual scientists, activists, engineers are talking about?"; "how much are they engaging the "public" in this problem?
   - Epistemic agency: Students' awareness of their learning process, their knowledge growth, and their knowledge gaps. How are the AI-enabled analytics allowing students to access to an accurate picture of their idea growth and not just a "score" of their work?
   - KB discourse leading to Rise-above: Redefining the role of experts in the learning environment. How do the AI-analytic provides visualizations that bridge the expert-novice chasm and support the removal of the hierarchical concept of expert answering students questions or expert judging students' question, but having experts as part of the community.

   Which aspects of knowledge building are augmented?
   - Social: student motivated to adjust their social interaction to learn more.
   - Cognitive & Metacognitive: Reflect on learning, interaction and "thinking" pattern
   - Emotional: Self-awareness and monitoring of emotions when engaged in knowledge work. When putting together, how these multiple dimensions (social, cognition, meta-cognition, and emotions) provide students with a new understanding of their ability and contribution which is the essence of 21CC. How these new understand then give students, regardless of their ability and age, the confidence to continue to contribute, to ride on their strength but also to work on their weakness. E.g. one who is a stronger thinker (providing good resource) but another could be more reflective of the dynamic of the group and asking more question about what to do next and in totality, how such heightened awareness of these two students within the community provides a platform to democratize the learning process.

   How does this augmentation enable the advancement of knowledge building beyond the current methods?
   - We are exploring various psycho-socio dimensions of knowledge building as well as integrating online and face-to-face interaction data. We advocate that knowledge building pedagogy and technology shape the culture of learning in class then students should behave, think differently throughout the online, face-to-face and even out of the class environment. The limitation of understanding students' thought through their post is potentially broken down by the introduction of AI. However, human interaction of mind and action in a knowledge building environment is so complex that the analysis is only possible if we worked through the previous few questions in a deliberate, rigorous and expansive manner. The current state of work in this still requires extensive manual triangulation to establish a near-accurate characterization of these knowledge building processes.

2. Which types of data are involved? (e.g., text, social interactions, cognitive interactions, voice, video, multimodal)?
   - LA/AI to create a meaningful connection between students' knowledge in class with that in the real world. LA/AI to support students in seeing their work in class connected to that in the real world.
   - Visualization of students' vocabulary, their emotional states that reveal insights of the learning process that might not be obvious to the learner or the teacher (e.g. perplexity)
   - Information about the process of learners' thinking and knowledge formation as it happens in a synchronous and asynchronous environment.

- Physiological data of students of heart-rate to help them manage their various emotions, from academic emotion to epistemic emotion.
- Multimodal data in the form of audio, video (of various granularities), physiological data, were collected and the analyses were shared with students throughout the two-day event.

Which types of analytics / AI are used?

- Quantitative: Number of notes written, read, replied, build-on.(For group post – we take the total number of writings and readings for the level of online interaction.
- Structure of online interaction – build-on.
- Content analysis of online & offline interaction: The content analysis can complement the type and level of interaction than the quantitative analysis.
- Social network analysis of online interaction. SNA visualizes learning processes through group members' interaction; structure, flow, and processes of interaction (e.g. centrality).
- Continually seeking coherence is what is important the design and practice, what is sound practice according to the principles, and most importantly, what impact do we want to create (Align with Q1).

How are the results of the analytics / AI presented? Who use the results (students, teachers, researchers)?

- Visualisation and outcomes of learning made available to the teachers, students, for discussion and self-reflection and these visualizations will be the object of meta-discourse. For teachers, these analytics will be used as data to make decisions about future actions; for students, it could be a metacognitive activity.

This set of questions has helped the researchers in determining the source of data, type of data, target audience of analytics, and types of analysis to be conducted.

## Conclusions

This short review and discussion show the emerging work in the knowledge building community in the use of analytics or AI to augment the knowledge building process. Knowledge building differentiates from other CSCL or constructivist pedagogies by engaging students directly in knowledge work. Our understanding and practices of knowledge building should also be advancing in a perpetual self-renewing way because knowledge creation is a future-oriented progressive endeavor that theoretically, should not have an end-point. Moving forward, we propose a set of questions to consider when developing and investigating the development of how knowledge building can be augmented by analytics and AI. This set of guiding questions is developed to first ask about the principles and aspects of knowledge building being investigated, and then the types of data and analytics or AI that will be used. By focusing on knowledge building principles is to avoid using AI to replace human intelligence in guiding knowledge building work or prescribing pre-determined actions, doing so will be running against the very purpose of principle-based approach and developing students' capacity in knowledge work. We recommend focusing on how human (students and teachers) could work in intellectual partnership with computers that generate timely insights from data, to engage in knowledge building more efficiently and effectively.

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