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# Determining Quality and Distribution of Ideas in Online Classroom Talk using Learning Analytics and Machine Learning

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**ABSTRACT:** The understanding of online classroom talk is a challenge even with current technological advancements. To determine the quality of ideas in classroom talk for individual and groups of students, a new approach such as precision education will be needed to integrate learning analytics and machine learning techniques to improve the quality of teaching and cater interventive practices for individuals based on best available evidence. This paper presents a study of 20 secondary school students engaged in asynchronous online discourse over a period of two weeks. The online discourse was recorded and classroom talk was coded before undergoing social network analysis and k-means clustering to identify three types of ideas (promising, potential, and trivial). The quality and distribution of ideas were then mapped to the different kinds of talk that were coded from the online discourse. Idea Progress Reports were designed and trialed to present collective and individual student's idea trajectories during discourse. Findings show that the majority of ideas in exploratory talk are promising to the students, while ideas in cumulative and disputational talks are less promising or trivial. Feedback on the design of the Idea Progress Reports was collected with suggestions for it to be more informative and insightful for individual student. Overall, this research has shown that classroom talk can be associated with the quality of ideas using a quantitative approach and teachers can be adequately informed about collective and individual ideas in classroom talks to provide timely interventions.

**Keywords:** Precision education, Machine learning, Learning analytics, Idea Identification and Analysis (I2A), Idea Progress Reports (IPR)

## 1. Introduction

In an era of unprecedented change and technological advancements, learning analytics has emerged as a nascent field that advance the understanding of learning processes (Siemens, 2013). Apart from using insights to provide teachers with timely but short-term interventions based on teaching and learning experiences, the true test in the long term would be to demonstrate how analytics can impact student learning and teaching practices (Gašević, Dawson, & Siemens, 2015). The larger and more effective goal will be to achieve personalized learning in current forms of mass public education systems while being cost-effective, which means avoiding running into Bloom's 2 Sigma problem (1984) that looked for methods of group instruction that can be as effective as personalized tutoring. Personalization of learning therefore remains a non-trivial task and although it has become more feasible with advanced technologies, efforts to maintain and scale best efforts past individual case studies of classes or schools, however, remain arduous.

The concept of precision education, as Hart (2016) explained, seeks to provide researchers and practitioners with tools to better understand complex mechanisms that hinder personalization at scale, allowing for a more effective approach to education. Similar and inspired by the Precision Medicine Initiative (Collins & Varmus, 2015), the creation of data would be necessary for gaining better understanding at the individual level, but such data is already prevalently abundant in the educational context and presents the next challenge: How to analyze and interpret an immeasurably large amount of student-related data to benefit students at the individual and micro level.

This challenge is familiar in communal discourse settings, where individual student interact, discuss, and share their ideas with each other in online discourse, creating an immense amount of textual data which traditional analytical methods have made attempts to process, albeit with partial success and trade-offs at scale. Teachers may try reading most, if not all, of the classroom discourse to gain a rudimentary understanding of student understanding but keeping track of ideas contributed by various students across the whole discourse is no mean feat. The fact that researchers have to select certain models and techniques to deal with subsets of data indicates that there is still difficulty in handling big discourse data. As part of the ongoing Fourth Industrial Revolution that has fundamentally transformed the scale, scope, and complexity of how people live, work, and study, the response to it must be integrated and comprehensive, to include all stakeholders from civil society to academia (Schwab, 2016). This industrial revolution is disruptive in almost every industry and country, led by emergent technologies such as Artificial Intelligence (AI) and other technological advancements such as learning analytics and machine learning techniques. With new affordances from novel methodologies and developments, it is now possible to review classroom data and analyze it with a contrasting perspective and under a different scope. Attention and emphasis can also be shifted from communities to individual for garnering deeper insights of how teaching practices and student learning can be improved on the individual, classroom-wide, and institutional levels.

This study adopts an "Idea Identification and Analysis" (I2A) methodology proposed by Lee, Tan, and Chee (2016) that was later improved in further iterations (Lee & Tan, 2017a; Lee & Tan, 2017b; Lee & Tan, 2017c). The I2A methodology identifies components of abstract entities such as ideas in discourse from online classroom talks, using a combination of learning analytics, social network analyses, and machine learning techniques. The resulting classification of ideas from discourse allows promising ideas in discourse to be differentiated from less promising or trivial ideas, so that teachers are able to focus on critical ideas that can advance lesson objectives in time-constrained lessons. In essence, although teachers may be conscious of different kinds of classroom talks (Mercer, 2008), they are however unable to delve deep into the discourse to gather insights of students' ideas with limited resources. The I2A methodology can be used to inform teachers about students' ideas at any point in time during an online discourse and through this study, this information can also be made available to individual student through summaries, such as an Idea Progress Report.

The research question guiding this study is: "How can learning analytics, machine learning, and Idea Progress Reports be used for determining the quality and distribution of ideas in different classroom talks to inform personalized interventions?"

## 2. Context and approach

### 2.1. Precision education as a new challenge for AI in education

Precision education is currently considered a new challenge of applying emergent technologies, such as AI, machine learning, and learning analytics for improving teaching quality and students' learning outcomes (Yang, 2019). The goals are aplenty in literature with a major focus on identifying at-risk students to provide timely interventions (e.g., Lu et al., 2018) and to enhance student outcomes through greater predictive accuracy (Kuch, Kearnes, & Gulson, 2020). The eventual objective is to tailor preventive and interventive practices to individuals based on best available evidence (Cook, Kilgus, & Burns, 2018).

Precision education in other research fields such as healthcare has moved emphasis from population-wide usage towards personalized medical care with the use of AI, such as in the field of radiology (Duong et al., 2019). Precision education has also emerged as an important aspect in the fields of policy sociology that takes into account data based on psychology, neuroscience and genomics (Williamson, 2019), as part of advocation by international organizations, such as OECD, to transmit scientific evidence into education policy and practice (Kuhl, Lim, Guerriero, & Van Damme, 2019)

In the field of education research, several studies have used context personalization (e.g., Bernacki & Walkington, 2018), by incorporating students' individual out-of-class interests into learning tasks so as to positively affect students' situational interests and their learning in mathematics. Other studies (e.g., Lin et al., 2017) have also extended this research to the field of computational thinking, by examining how customization of tools (e.g., character customization) can influence factors related effects, such as transfer, self-efficacy, and motivation. These studies were conducted as part of the hypothesis that customization can lead to higher and better learning outcome and could also provide greater flexibility for students who are less adaptable to new learning styles, thus reducing the chances of them being left behind.

### 2.2. The focus on ideas in discourse

Precision has been argued to require new data production and aggregation frameworks to measure and intervene, while drawing on established subjectivities to present newer insights (Kuch et al., 2020). Apart from previous approaches of developing customizable software features and handling of personal data from newer sources, it is feasible to start looking at the development of tools and methods that capture data, analyze, and present insights related to abstract entities such as ideas, which was previously not possible without state-of-the-art methodologies and techniques.

In an educational setting, individuals interact and share ideas to collaborate and build their understanding of the world, by treating ideas as real things, as objects of inquiry and improvement in their own right (Scardamalia & Bereiter, 2003). An idea, is hence, more than just a unit of thought, but rather the provision of epistemic function to represent something else with an ability to improve and extend beyond itself. When situated in a discourse, ideas can represent something pictured in mind, part of a concept, or as a way of explaining phenomenon. At the initial stage, ideas are, however, represented in preliminary forms with uncertain prospects (Chen, Scardamalia, & Bereiter, 2015). In order to achieve a higher level of understanding, ideas that are improvable and capable of moving the community in a forward direction are highly desirable and these ideas with *promisingness* (Chen, 2014) are critical for ensuring productive and effective classroom talk, especially when posed with authentic problems.

Ideas were differentiated in Lee's et al. (2016) work using three factors, namely, (a) the relevancy to the community; (b) the sustainable level of interest to the community; (c) the likely impact of the idea on discourse. The same research also defined different types of ideas in discourse, noting that promising ideas are of great relevancy to the community, sustains interests of the community, and are therefore worth pursuing. Potential ideas are relevant to some extent but suffers from waning communal interest over time, therefore requiring scaffolds and interventions to maintain communal interest. Last, trivial ideas are of minimal relevance and interest to the community.

### 2.3. Relating ideas to classroom talks

Mercer (2008) described in his work about talk as one potential influence on the development of students' knowledge and understanding. Talk can be used as a tool for learning and the focus should be on the quality of classroom talk, arguing that the social interactions and collaborative activities in the class can provide valuable opportunities for learning. For example, on the one hand, *exploratory talk* is defined to be a "joint, coordinated form of co-reasoning, in which speakers share relevant knowledge, challenge ideas" (Mercer, 2008, pp. 95). On the other hand, *disputational talk* consists of cycles of assertion and counter-assertion, forming sequences of short utterances that rarely include explicit reasoning (Mercer, 1995). *Cumulative talk* is the middle ground of exploratory and disputational talks, where students share some knowledge and ideas but in an uncritical manner with little evaluation.

In this study, the aim is to show that learning analytics and machine learning techniques can aid the investigation of ideas containing different levels of *promisingness* in discourse, a challenging process considering the nature of unstructured textual data. The distribution and quality of ideas can then be mapped to different kinds of talk that emerge from online classroom discourse.

### 2.4. Social network analysis and machine learning techniques in discourse analysis

Social network analysis (SNA) is an appropriate practice for analyzing social patterns of leaners and community structures (Scott, 1988). However, Oshima's et al. (2007) work found that SNA may be insufficient for examining community knowledge advancement through students' collaboration and interaction networks. In order to focus on the patterns of emerging ideas in discourse, the I2A methodology involves the generation of social networks based on bipartite relationships that associate keywords, discourse participants, and discourse units, which are then used to calculate the network measures of the discourse unit network. The study of indicators such as "centrality" determine the level of interaction between students (Wortham, 1999). Among common methods of measuring centrality, this study uses two conventional network measures, namely the betweenness centrality (BC) and the degree centrality (DC). The role of BC for any given node refers to the degree of importance of the node in helping to connect ideas in a discourse, whereas the DC is a good measure of connectivity from the node to the rest of the network.

Both BC and DC measures were similarly used in a separate study (Oshima, Oshima, & Fujita, 2016) to distinguish epistemic actions for awareness of lack of knowledge in students. For this study, the goal is to aid the identification of promising ideas from classroom discourse. The process whereby participants share and exchange information often leads to the creation of meaningful links between normal communicative speech and usage of important keywords. Therefore, since ideas are considered to be central to discussions and for mediating opinions among students, the examination of the BC and DC measures can provide insights on the degree of sharing and level of communication by students within a discourse network.

In recent years, learning analytics and machine learning were more frequently used for analyzing discourse. Examples include Discourse-Centric Learning Analytics (DCLA; Knight & Littleton, 2015) and methods that are either semantic based (e.g., Hsiao & Awasthi, 2015) or involve topic models, such as those built on Latent Dirichlet Allocation (LDA; Blei, Ng, & Jordan, 2003). Extended variations include structural topic modelling, which integrates computer-assisted text processing (Roberts, Stewart, & Tingley, 2013). Alternative methodologies have also emerged in recent times and are able to process multi-dimensional data. Examples of these methodologies include machine learning techniques for automatic text classification (e.g., Garrard, Rentoumi, Gesierich, Miller, & Gorno-Tempini, 2014), clustering techniques with Part-of-Speech (POS) tagging (e.g., Owoputi et al., 2013; Lamar, Maron, Johnson, & Bienenstock, 2010), and Natural Language Processing (NLP) related methods. With multiple sources of data and features to choose from, these studies have narrowed their focus to specific types of context, data, and instruments, in order to make sense of the data and analyse the various impacts on learning. Only a few methodical approaches, including the approach taken in this study, attempt to conduct idea analysis and discern the quality of ideas in discourse to further understand how classroom talk can be associated with the quality of ideas to adequately inform teachers and provide timely interventions.

### 2.5. Idea Progress Report as teacher feedback to individual student

Prior research (e.g., Tunstall & Gsipps, 1996; Van den Bergh, Ros, & Beijaard, 2012) have shown that teacher feedback to students is crucial for enhancing and progress in student learning. Teacher feedback can be verbal or written and exists in different forms, such as reports, rubrics (Wollenschläger et al., 2016), or corrective responses (Zheng & Yu, 2018). Teacher feedback should be related to meta-cognition, social learning, and learning goals but such instances are still rather scarce in practice (Van den Bergh et al., 2012). In this study, to ensure that teachers are provided with sufficient information to cue critical and timely interventions for students, an artifact in the form of an Idea Progress Report (IPR) was designed and trialed.

The IPR is a feedback tool that was designed with precision education in mind. The goal was to provide adequate information and assistance to the teacher to make informed and timely interventions for students who were participating in knowledge building activities within the classroom. In preparation for this study, data from prior research was reorganized and analyzed based on the I2A methodology (Lee et al., 2016; Lee & Tan, 2017a) and with consideration of Mercer's three kinds of talks (2008).

## 3. Methodology

### 3.1. Participants

A total of 20 secondary school (Grade 8) students were involved in this study under the instruction of an experienced teacher. He was pedagogically trained and has been teaching for nearly a decade at the point of the study and was able to facilitate computer-aided and knowledge building lessons effectively.

### 3.2. Dataset and settings

The dataset in this study includes 101 notes written by students on the Knowledge Forum (Scardamalia, 2004), an online discourse platform that supports knowledge building. These notes are online postings written by the students, consisting of their ideas, discussions, and arguments about an authentic problem, which is "how and why is an uncle suffering from cardiovascular problems" and related to the science topic on the "human circulatory system." The focus of this study is the textual content of the notes, which was extracted, cleaned, and anonymized to protect the identities of students. The online discourse was recorded over a period of two weeks and held at a computer-aided environment in the same secondary school.

### 3.3. Determining discourse groups and types of talk in online discourse

To determine the kind of talks that could be present in an online and asynchronous discourse, a virtual space on the Knowledge Forum was hosted for students to contribute and build on each other's responses (see Figure 1).

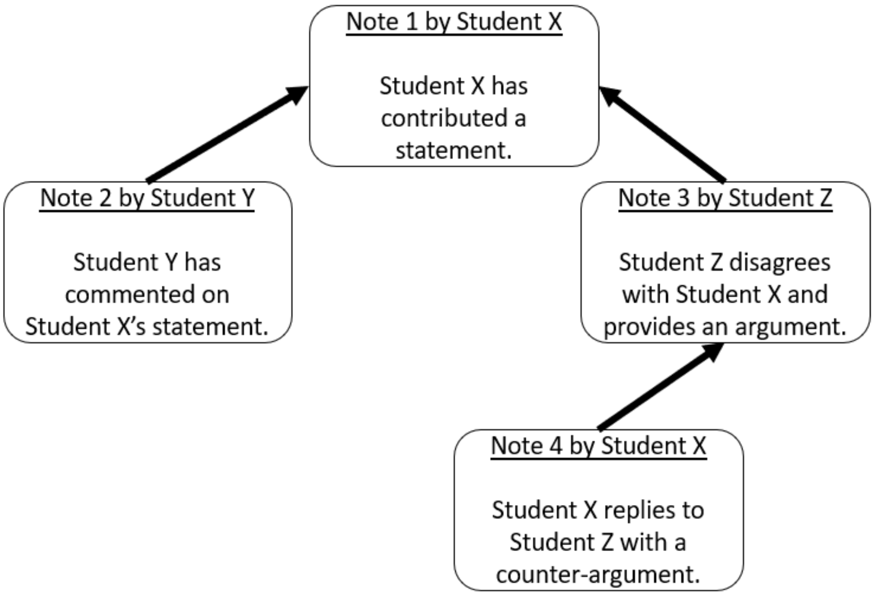


*Figure 1.* Example of how students build on each other's statements, claims, or ideas in Knowledge Forum

The replying and quoting mechanism of threaded discussions is commonly seen on discussion boards and forums, often presented in a top-down and linear format. When students are provided with a virtual space (also known as a "view") on the Knowledge Forum, students could read other student-written notes on the same view and visually estimate the width and depth of discussion as they participate, without clicking into the discussions. Since Knowledge Forum notes are movable features on the virtual space, students could move their notes around the virtual space to form separate discussion groups with their own peers. This feature does not impact the overall quality of classroom discourse and further enabled analysts to visualize and spatially identify discourse groups in classroom discourse, different from conventional methods that may need to pre-define discourse groups through assignment or conversational analysis of turn-taking.

To illustrate this point, Figure 2 shows a screenshot of how discourse groups (circled and labelled) can be visually identified on a Knowledge Forum view, based on how threads are being initiated and continued with notes building on each other (represented by single-headed arrows) by multiple students. The talks in these individual discourse groups were then examined and qualitatively coded based on Mercer's classification of talk (Table 1).

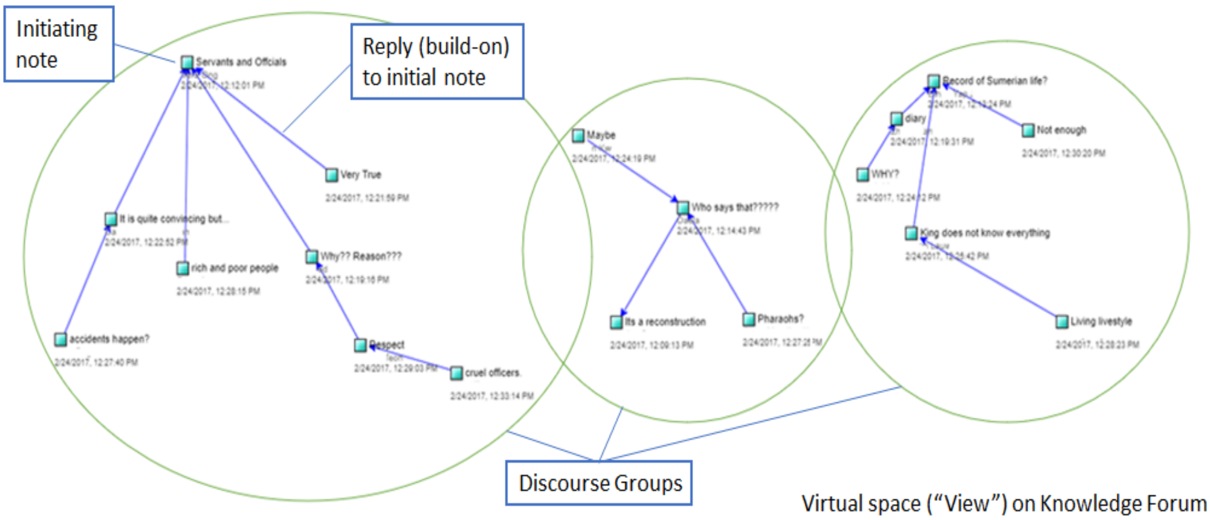


*Figure 2.* A screenshot on Knowledge Forum showing how students can estimate the depth of discussion at a glance and how analysts can visually identify discourse groups

*Table 1.* Mercer's (2008) classification of classroom talks and examples of sequences within the talks

| Types of classroom talk | Observations | Examples of sequences from this study's dataset (Students' names are represented by alphabets) |
|---|---|---|
| Disputational | • Cycles of assertion and counter-assertion, forming sequences of short utterances<br>• Little effort to pool resources or offer constructive ideas<br>• Competitive instead of cooperative environment | A: "What happens if it is normal?"<br>B: "What is it?"<br>A: "Like, it is a verb, that's all."<br>B: "What does it refer to?"<br>A: "Ok, fine! It refers to the pain." |
| Cumulative | • Students are accepting of other ideas but in an uncritical manner<br>• Some sharing of knowledge is present with some build on<br>• Repetition of each other's ideas with little evaluation involved | A: "What will be the consequences if he continues to eat unhealthily?"<br>B: "His arteries will keep on collecting fats."<br>C: [quotes B's reply] "Uncle's arteries will continue on collecting fats and his arteries will become blocked and it will burst."<br>D: "My theory – His condition will definitely get worse if he continues eating unhealthily." |
| Exploratory | • Students actively listen to each other and share ideas<br>• Ideas may be challenged with reasons<br>• Joint, coordinated form of co-reasoning | A: "How will the operation be done?"<br>B: "A balloon will be inserted into his coronary artery and inflated…"<br>C: "All these procedures increase blood supply to your heart but they do not cure coronary heart disease"<br>A: "So what cures coronary heart disease?"<br>C: "Treatments include lifestyle changes, medicines, medical procedures." |

### 3.4. Idea Identification and Analysis using social network analysis and clustering technique

The Idea Identification and Analysis (I2A; Lee et al., 2016) methodology was conducted to identify and classify ideas in the online discourse, serving as an indication of communal understanding and a quantifiable measure related to the quality of ideas that were proposed and discussed by the students. The methodology is split into two phases.

The first phase involves text mining to discover keywords that are basic units of analysis that can also indicate partial resemblance of ideas when present in groups, phrases, or sentences. A text miner (Reategui, Epstein, Lorenzatti, & Klemann, 2011), based on the work of Schenker (2003), was adapted for educational purposes and mines the textual discourse data to generate a list of related conceptual keywords. To enhance the accuracy of the miner, an in-built thesaurus was included to ensure that stop words, noun markers (e.g., determiners like "the," "this"), pronouns such as "his," "her," and non-unique synonyms (e.g., using "student" to represent "students," "pupils," and "children") are excluded from the final list of keywords. The resulting list of keywords would then serve as inputs for the second phase of the methodology.

The second phase of I2A utilizes a mixture of social network analysis and machine learning to pinpoint the location of ideas in the discourse and determine the quality of ideas via unsupervised learning. A social network analyzer (KBDeX; Oshima, Oshima, & Matsuzawa, 2012) was used to generate social networks based on bipartite relationships that associate keywords, discourse participants, and the discourse units, which in this study, refer to notes written by students on the Knowledge Forum. A discourse unit (DU) may exist as a standalone note containing statements or claims written by students but can also be found as part of a threaded sequence as shown in Figure 1. For example, a student who posted new information in a note (DU1: "Clogged arteries result from a buildup of a substance called plaque on the inner walls of the arteries…"), was built on with a following note (DU5: "I need to understand – how does this affect us?"). These DUs are often chronologically labelled according to the time of posting to the discourse space. The relationships among the social networks are then analyzed to calculate conventional network measures, which in this study refers to the betweenness centrality (BC) and degree centrality (DC). These two network measures are utilized together in this study, resulting in the reorganization of discourse data onto a two-dimensional variable space plot. This variable space plot containing the network measures is referred to as the DC-BC graph and provides a discourse unit visualization overview, where discourse units are shown side-by-side on a same plot during any point in time of the discourse. This plot is shown in the findings and provides a visual method of estimating the *promisingness* of ideas.

The k-means clustering algorithm can use the same plot to determine idea quality, by being implemented to the DC-BC graph to form “k” number of clusters that represent the three types of ideas present in this study. While the use of other similar machine learning algorithms such as the supervised k-nearest neighbor (k-NN) algorithm was contemplated, the k-means algorithm was selected due to its unsupervised nature and with consideration of the limited datasets available in this study. This study focused on three likely types of ideas in discourse and by using Euclidean distance as the distance metric in determining the global silhouette peak value at an optimal “k” value, the value of “k” in this study was determined to be three, allowing the final clustering results to show the type of ideas that likely reside within individual DUs. Last but not least, the categories of ideas estimated via clustering were qualitatively analyzed and verified.

### 3.5. Qualitative determination of idea quality in various online classroom talk

Based on Mercer’s classification of talk (Table 1), the talks in the discourse groups were qualitatively coded by two researchers who have extensive experience in working with knowledge building discourse. Both researchers were first provided with a list of discourse groups, with each group containing a thread of student-written notes. The notes were then qualitatively scrutinized to determine if there are observations or indications in the talk similar to the observations and examples shown in Table 1, which are then used as evidence for labelling the discourse group accordingly. The resulting inter-rater reliability was calculated with the remaining differences between the two raters resolved after further discussion, culminating in a final determination of the different kinds of talk in the knowledge building discourse. After the various discourse groups were qualitatively coded and I2A was conducted on the discourse data, the quality of ideas that was determined through the k-means clustering technique was mapped to the coded classroom talk. This provided a sense of how different quality of ideas in discourse may influence or lead to certain kinds of classroom talk, and whether students will be inspired or discouraged from building on each other’s ideas.

### 3.6. Design of Idea Progress Report

After the distribution of ideas in DUs was determined, this information was provided to the teacher as feedback in the form of an Idea Progress Report (IPR). The IPR served as a one-page summary describing statistics and details of a student’s idea trajectory as a member of the discourse community. The various sections of the IPR that are shown in Figure 3 provide critical details for informing students and to recognize their efforts in the crafting and dissemination of ideas within the community. These details may include a profile of an individual student, the date-time and statistics of knowledge building efforts on the Knowledge Forum, a graphical representation showing the student’s efforts relative to other students, and several pointers that highlight the important contributions to the community.

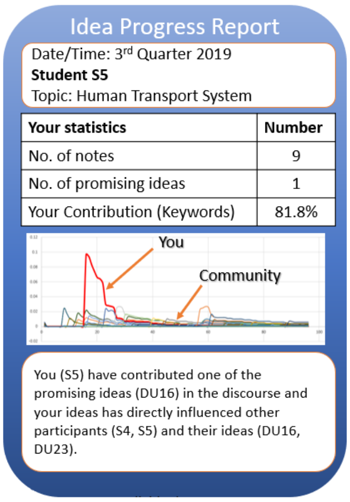


*Figure 3.* A screenshot of the one-page Idea Progress Report that can be issued to individual student, based on their efforts and work on ideas during the online discourse

## 4. Findings and discussion

This section details findings from the study in a sequential manner. First, results from the qualitative coding of the discourse groups is shown, followed by the results from the implementation of the k-means clustering on a variable space plot containing the network measures from all of the DUs in the discourse. A condensed qualitative analysis is presented for selected DUs to explain how ideas in the discourse are classified in a certain manner, before lastly, an aggregated breakdown of ideas that are found in different classroom talks is listed with suggestions on possible reasons why some types of ideas are in found in different kinds of classroom talk.

### 4.1. Coding of discourse groups

A total of 13 discourse groups, with the smallest group consisting of at least two notes, were identified on the Knowledge Forum view. These groups comprise 50 of the 101 notes on the Knowledge Forum view, with the remaining 51 notes belonging to standalone notes that contain claims or statements from individual student that were not built on by other students or included as part of discourse groups. The notes in the discourse groups were qualitatively coded between two expert researchers with an inter-rater reliability rate of 84.6%, whereby the remaining differences between the two raters were resolved after further discussion, culminating in a final and qualitative determination of labels for various kinds of classroom talk in knowledge building discourse.

There were altogether six instances of exploratory talk, five instances of cumulative talk, and two instances of disputational talk, as shown in Table 2. Considering that the series of lessons over the two weeks were constructed to give students opportunities to build knowledge, the overall atmosphere was conducive for sharing of ideas and the environment was purposefully constructed to be psychologically safe so that students are able to propose and share ideas freely without fear of assessments or repercussions. Therefore, the chances of encountering large amounts of exploratory and cumulative talk was not unexpected. The final section of the findings (Table 3) shows a breakdown of the distribution and quality of ideas for the different kinds of talk that surfaced in the discourse.

*Table 2.* Number of notes (DUs) in each discourse group and how each group was coded

| Discourse group no. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Number of DUs in group | 3 | 3 | 2 | 5 | 4 | 3 | 10 | 5 | 4 | 2 | 2 | 5 | 2 |
| Coded talks | C | E | C | C | E | C | D | E | E | C | E | D | E |

*Note.* The three types of talks were coded using the first letter of each type of talk, namely, "E" for Exploratory, "C" for Cumulative, and "D" for Disputational.

### 4.2. Classification of ideas from clustering of discourse units

Once the social network analysis was used to calculate the pairs of DC and BC values for all discourse units, the pairs of values were then plotted on the variable space plot in preparation for k-means clustering. Figure 4 shows the position of the markers on a single variable space plot, with each marker (represented by a hyphen) representing an estimate of the quality of ideas in the individual discourse units. For example, a discourse unit in the top right corner of the DC-BC graph with relatively higher DC and BC values indicates that the discourse unit is likely to contain ideas that are promising, as compared to a discourse unit at the bottom left of the DC-BC graph, which is likely to contain trivial ideas.

The k-means clustering was subsequently conducted to confirm the estimates of the discourse units. Three clusters are formed as shown in Figure 5, suggesting that the three separate clusters could be labelled as containing promising, potential, and trivial ideas respectively. From the clustering results, the blue crosses represent discourse units containing promising ideas, with the green diamonds representing discourse units containing potential ideas, and the red dashes indicating discourse units that contain trivial ideas. The centroids created due to the clustering technique also help to visualize group-centric positions of the three clusters within the entire discourse. By using the clustering technique, the quality of ideas in each discourse unit was determined in a timely and possibly scalable manner.

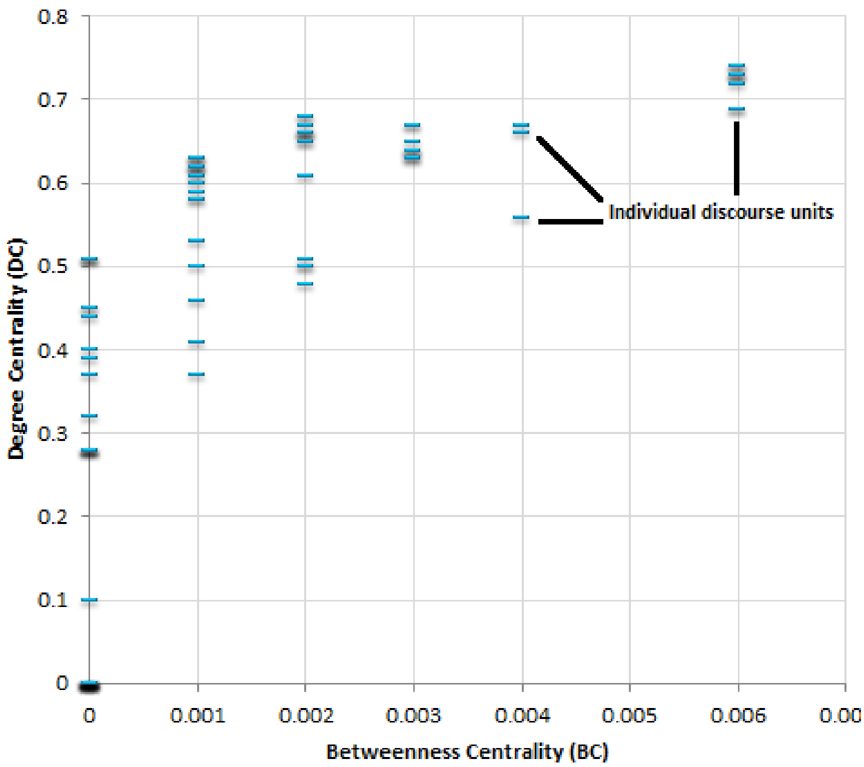


*Figure 4.* A DC-BC graph showing the estimated *promisingness* of ideas in each discourse unit at the end of the discourse

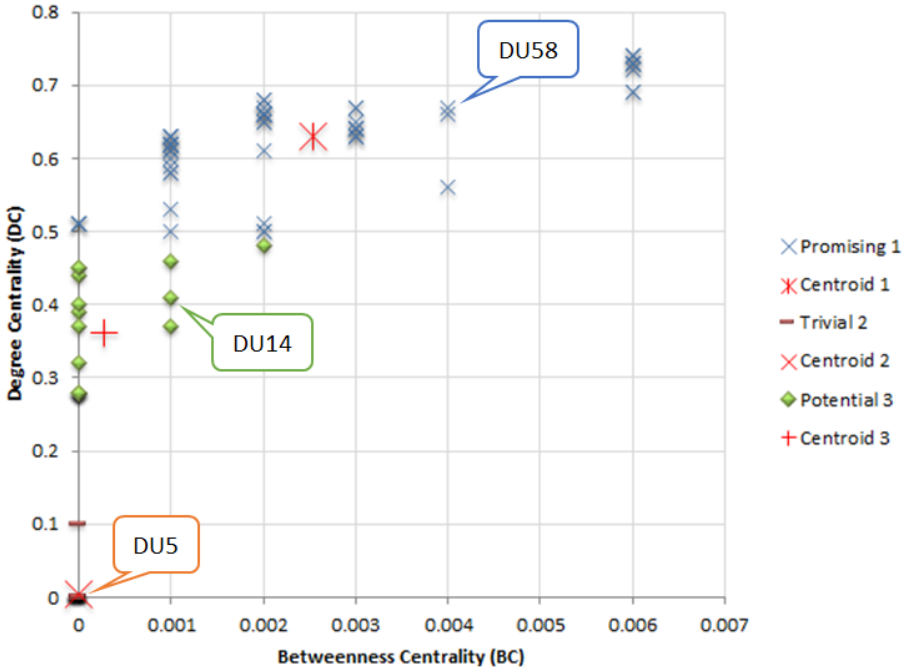


*Figure 5.* A DC-BG graph showing discourse units positioned in three clusters after k-means clustering was conducted on the discourse units at the end of discourse

### 4.3. Verification of idea quality in discourse units using qualitative analysis

Since training data was not utilized in this study due to the unsupervised nature of k-means clustering, it was noted that instead of a k-fold cross validation, a qualitative analysis was conducted to verify the quality of ideas against the qualitative content in the discourse units. The following are excerpts of the qualitative analysis for three discourse units (annotated on Figure 5) that were determined to contain trivial, potential, and promising ideas respectively.

Starting with DU5, this was a question contributed by student S3, who was trying to understand, "How does this affect us?" The reference of "this" refers to a set of new information contributed by student S1 prior to the query, which by itself was considered to contain promising ideas. However, due to the lack of relevancy and interest or impact on the discourse, DU5 was considered to be written solely as an attempt to seek clarity and was trivial.

In response to a new inquiry, another student S6 asked "Is the plaque blocking the coronary artery the same as the plaque in the teeth?" and DU14 was a response by student S1 who answered "Surprisingly, there is no link between dental plaque and the plaque build-up that attaches to your arteries. If there was, then each swallow and sip would be killing you slowly." This discourse unit was an interesting take on how students respond to each other with some relevant information and managed to sustain some interest among the group of students for a period of the discourse, resulting in it being considered to contain potential ideas that can be further built on.

Promising ideas in discourse, such as ideas found in DU58 and contributed by student S5, sought to build on previous replies and improve on each other's ideas. The ideas in DU58 improved on a current theory in DU56 that "cigarette smoking increases the risk of coronary heart disease by itself and that smoking increases blood pressure, decreases exercise tolerance and increases tendency for blood to clot", by proposing a better theory that "it is the buildup of fatty material (atheroma) which narrows the artery that can cause angina, a heart attack or a stroke." Examples of such promising ideas are often relevant to previous inquiries and context, sparking students' interests and encourages the sustenance of discussion that impacts subsequent discourse over a longer period of time.

Overall, the presence of different types of ideas in the individual discourse units can be determined using the DC-BC graph and k-means clustering, with findings showing that identified promising ideas can be further build on to sustain knowledge building discourse.

### 4.4. Identifying breakdown of ideas in different online classroom talk

The findings from the clustering results were subsequently used to form a breakdown of ideas in the various types of classroom talks. Table 3 presents a breakdown of the distribution and quality of ideas that emerged from different types of online classroom talk.

*Table 3.* A breakdown of the distribution and quality of ideas in different types of classroom talk

| Types of classroom talk | Types of ideas | | |
|---|---|---|---|
| | Promising | Potential | Trivial |
| Disputational | 6.7% | 33.3% | 60.0% |
| Cumulative | 46.7% | 20.0% | 33.3% |
| Exploratory | 75.0% | 5.0% | 20.0% |

From the findings in Table 3, there is a clear split between the types of ideas that exist in different types of classroom talk. Disputational talk tends to contain the least amount of promising ideas whereas three out of four ideas in exploratory talk are considered promising. Most of the trivial ideas in the discourse also exist in disputational talk, while cumulative talk contains some of each type of ideas, with nearly half of the ideas being promising.

Looking past the numerical statistics, examples of each type of classroom talk were examined with a qualitative lens using the coded labels. For example, discourse group 12 was coded as disputational talk, consisting of mostly short interactions, statements, and agreements without explanations, such as "What is it?" "It is a verb, that's all" and "Ok fine." The content from the discourse units in discourse group 12 revealed little attempts by students to work together or to share their ideas, representing a dearth of promising and potential ideas.

An example of cumulative talk was found in discourse group 4, which started off with a question about the consequences of a person who continues to eat unhealthily. Students then shared their ideas and knowledge, but were mostly doing so in an uncritical manner, by simply building onto existing ideas by adding theories or opinions without evaluation. At times where comparison of theories or opinions were conducted by students in the discourse group, the evaluations then transited into part of a potential or promising idea that further encouraged discussions among the discourse group, thus reflecting the fair share of promising and potential ideas that exist in cumulative talk.

Discourse group 5 is an example of why exploratory talk tends to consist a majority of promising ideas. The talk was initiated with the proposal of a theory and relevant explanations about the functionalities of red blood in the human body. The proposal was then built on with external resources such as website links that students could use to aid their understanding. Some students decided to challenge the ideas in the first note (theory proposal) and compare with their own ideas, while other students in the discourse group deliberated and expanded on specific functionalities of blood components, leading to a better general understanding of blood components. There was a culture of respect for each other's ideas that was similarly observed in other discourse groups coded as exploratory talk, such as groups 2, 8, 9, 11, and 13. There was also no bashing of opinions, so students were more at ease to share relevant information and everyone was encouraged to contribute to the exploratory talk.

In summary, it is likely that the presence of promising ideas contributed to exploratory and cumulative talk that can be productive for students, while disputational talk contains the bulk of trivial ideas. However, the latter kind of disputational talk cannot be entirely discounted and ignored because exploratory and cumulative talk cannot be expected to occur at every turn of discourse. Therefore, as evidence in this study has also shown, promising ideas do still occur in disputational talk and teachers should take note not to totally ignore this kind of talk in the classroom but continue to monitor the discourse with discretion.

### 4.4. The trial of Idea Progress Report in this study

Given the breakdown of the distribution and quality of ideas for different talks, the teacher can recognize ideas and discern the level of understanding in a classroom from a collective or individual point of view. Moving one step ahead, the deployment of the Idea Progress Report (IPR) can provide a more precise and customized level of student information for teachers to provide personalized actions or interventions. The IPR prototype was trialed in this study at short notice and therefore, the IPR was not fully deployed as part of the lesson plan due to time constraints. Instead, the teacher presented the IPR to students as an optional source of information during lessons and feedback on how the prototype can be improved was garnered from both teacher and students.

The teacher was adamant that the design and maintenance of two versions of the IPR, namely the individual version for students and a collective version for the whole class, will be beneficial for teachers who do not have the time to analyze the whole discourse and for students who prefer a collective view of the entire discourse. Contrarily, some students felt that the collective version of the IPR was not useful to them but agreed that it would eventually be useful for the advancement of communal interests that may have a trickle-down effect of benefits for the students. These feedbacks are considered for improving the design of the Idea Progress Reports so as to make it more informative and insightful for both teachers and individual student in future studies.

### 4.5. Limitations of current study

Several limitations are acknowledged in this study. First, the provision of the breakdown, which shows the distribution and quality of ideas in various classroom talks, is considered to be indicative of possible predictive trends and not a direct representative of larger class sizes that can be easily replicated. Further, since the findings are based on a sample size of a single class discourse, the results may not be definitive at this point, but it is evidence-based and initial findings from other ongoing work has shown indications that this is an area that is worthy of exploring at scale. In line with efforts to encourage timely interventions and to provide students with personalized feedback, the work with teachers on the IPR will be continued to ensure that the reporting tool can be deployed within the limited time frame of lessons and curriculum, so that on-site data collection for idea analysis and IPR can be conducted in parallel during future studies.

## 5. Conclusion

In this paper, the concept of precision education has been applied to provide researchers and practitioners with tools to better understand complex mechanisms that provide a more effective approach to the understanding of ideas in online discourse, specifically during online classroom talk. Using social network analysis, learning analytics, and machine learning such as clustering techniques, three types of ideas were identified throughout discourse and were mapped to determine the distribution and breakdown of ideas in different classroom talks. The design and trial of Idea Progress Reports in the classroom also helped to highlight the fact that ideas in discourse can be used to inform teachers to deploy interventions for students who might be falling behind in lessons.

An analytical study of this nature is inconceivable a couple of decades ago, but with the emergence of nascent fields such as learning analytics and machine learning, it is inevitable that newer fields of research and methods can support novel forms of analysis and provide deeper insights on previous data that were almost impossible to process. From this empirical study, evidence have shown that it is possible to demonstrate how classroom talks can be associated with the quality of ideas in a quantitative manner. More so, this research has the potential to be used for predictive purposes in other aspects of precision education.

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