Varying Effects of Learning Analytics Visualizations for Students with Different Achievement Goal Orientations

by

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Thesis Submitted in Partial Fulfillment of the
Requirements for the Degree of
Master of Science

in the
School of Interactive Arts and Technology
Faculty of Communications, Art and Technology

SIMON FRASER UNIVERSITY

Fall 2015

Approval

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Degree: **Master of Science**

Title of Thesis: **Varying Effects of Learning Analytics Visualizations for Students with Different Achievement Goal Orientations**

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Abstract

Through advancements of Technology-Enhanced Learning an opportunity has emerged to provide students with timely feedback using Learning Analytics in the form of visualizations. To afford actual impact on learning, such tools have to be informed by theories of education. Particularly, educational research shows that individual differences play a significant role in explaining students' learning process. However, limited empirical research has investigated the role of theoretical constructs such as motivational factors that are underlying the observed differences between individuals. In this work, we conducted a field experiment to examine the effect of three designed Learning Analytics Visualizations on students' participation in online discussions in authentic course settings. Using hierarchical linear mixed models, our results revealed different effects of visualizations on the quantity and quality of messages posted by students with different Achievement Goal Orientations. Findings highlight the methodological importance of considering individual differences and pose important implications for future design of Learning Analytics Visualizations.

Keywords: Learning Analytics; Visualization; Achievement Goal Orientation; Online Discussions; Educational Technology; Personalized Learning

To my dearest parent,

Sharareh Atash and Saeid Shirazi,

For their unconditional love, encouragement and support.

Acknowledgements

I would like to express my deepest gratitude to my supervisors Dr.Marek Hatala and Dr. Dragan Gasevic. I consider myself incredibly lucky for having had the encouragement, guidance and endless support of two incredible supervisors who believed in me more than I believed in myself. Because of their support, my Master's journey turned out to be an unforgettable, fruitful, and life-changing experience.

Many thanks to all the brilliant members of our research lab for the delightful moments we spent together. In particular, I'd like to thank Srecko Joksimovic and Liaqat Ali for their help and moral support when times were tough. Special thanks also go Vitomir Kovanovic, Bardia Mohabbati, Mohsen Asadi, and Halimat Alabi.

Most importantly, I would like to thank my amazing family and friends who were there for me from the start to the end. None of this would have been possible without their unconditional love and encouragement.

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1 Introduction

Learning Analytics is considered a newly emerged area in Technology-Enhanced Learning research that draws on methods and techniques from diverse range of research fields including educational psychology, learning sciences, technology and information visualization [20, 27]. As defined in the first Learning Analytics and Knowledge Conference back in 2011[1], learning analytics is the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environment in which it occurs".

Learning analytics was initially focused on institutions to inform educators about students' engagement and academic performance, and to support their decision making to maintain students' retention. However, recently Learning Analytics have been realized as a particularly powerful and yet challenging opportunity to focus on learners' perspective and put these new learning tools in the hands of students to support their learning [53]. This can help address the long-known problems of students not consistently receiving relevant, timely and personalized feedback on their learning and as a consequence not engaging as active drivers and monitors of their own learning. One way of providing feedback to students through Learning Analytics is in the form of visualizations and dashboards.

A review of existing Learning Analytics Visualizations reveals that their design is mostly focused on theories of information design and their evaluations are mainly limited to students' self-reports of perceived usability and usefulness [8, 9, 28, 33, 43, 46, 55, 56]. Without careful consideration, these designs can lead to implementation of fragile and undesirable instructional practices by promoting ineffective feedback types and methods [27]. To afford an actual impact on learning, Learning Analytics Visualizations have to be

[1] https://tekri.athabascau.ca/analytics/

further informed by theories of learning sciences and educational psychology so they can encourage adoption of effective instructional and intervention practices [27, 66].

However, there is limited empirical research to date that have sought to investigate the actual impact of such visualizations and dashboards on students' learning in authentic course settings with respect to theoretical frameworks. Particularly, the role that individual differences play on using these visualizations and their effect on the learning behavior of different students has not been studied. Educational research shows that individual differences play a significant role in explaining students' learning process. This had led to rise of new learner-centric models of learning which re-identifies learning as being personal, self-directed and consider learners as the main drivers of their learning [10]. This suggests that the one-size-fit approach may not work well when designing Learning Analytics tools and visualization. Hence, it is important to consider the theoretical constructs – so called aptitudes – that shed light up on the observed differences between individuals [65]. Among all aptitudes, motivation remains as an important and yet complex personal factor that influences learning. Particularly, it is highlighted that "The real obstacle in education remains student motivation. Especially in an age of informational abundance, getting access to knowledge isn't the bottleneck, mustering the will to master it is." [2]

A learning environment where Learning Analytics Visualizations can be most useful are online discussions which are commonly exploited to support collaborative learning in distant and blended courses particularly at higher education level [2, 44]. Asynchronous online discussions can be seen as an environment in which learners can interact to build both collective and individual understanding through conversation with one another [38]. Despite all the potentials, online discussions don't always live up to their promises as they usually suffer from participation issues [45, 49, 57, 62, 67]. For this reason, providing learners with Learning Analytics in the form of visualizations to monitor their participation in online discussions can be supportive of productive engagement in discussions [66, 70]. As Learning Analytics is a relatively new area, further research needs to be done to develop a body of knowledge that could guide development and application of Learning Analytics tools including visualizations and dashboards. This research aim to

[2] http://chronicle.com/article/Why-Technology-Will-Never-Fix/230185/

add to the limited work that studies the effect of using Learning Analytics Visualizations on students' participation, and subsequently learning in online discussions. Particularly, the present work intends to investigate the role that aptitudes including motivational constructs play on using these visualizations and their effect on the students' participation.

To fulfill this goal, we conducted a controlled experiment to examine the effect of using different Learning Analytics Visualizations on students' participation in online discussions in authentic course settings. Within the course, students were asked to engage in an online group discussion task which was designed in accordance to research guidelines on effective design and facilitation of online discussions. In addition, student were assigned to an experimental condition in which they had access to one of three Learning Analytics Visualizations designed to help them inform on how they are doing in the discussion. To further investigate the role of aptitudes, particularly motivational constructs, an instrument was used to evaluate students' Achievement Goal Orientations, which is one of the most prominent theories of motivation in educational research and is defined as "the purpose of engaging in an achievement behavior" [18] (p.632). We collected log data of students' activities in online discussion platform including their interaction with the visualizations, as well as their questionnaire responses. Further, students' participation in online discussions was measured based on quantity and quality of posting behavior. The quality of posted messages was computed using some higher-level features of discourse using Coh-Metrix, a well-established computational linguistics facility. Hierarchical linear mixed models were used for statistical analysis.

Using this methodology, we primarily investigated whether the users of the visualizations were associated with different posting behaviors than the non-users. Further, we studied whether those who used the Learning Analytics Visualizations their level of usage influenced their posting behavior. Also we aimed at finding out the effect of different visualizations on students' level of engagement with the Learning Analytics Visualizations and its influence on their posting behavior. Finally, we studied how considering self-reported Achievement Goal Orientations affected the association between different Learning Analytics Visualizations and the above dependent variables.

The subsequent sections of this work are as follows. In Section 2, we provide a brief introduction to Learning Analytics situated within the context of Personalized Learning and aptitude constructs particularly Achievement Goal Orientation. Then, we

provide an overview of existing Learning Analytics Visualizations and draw on their limitations followed by Learning Analytics particularly intended for online discussions. Section 3 is focused on the methodology including experimental design and research questions, Learning Analytics Visualization designs, discussion activity description, experiment procedure and participants, and finally data collection and analysis. In Section 5, we conclude by detailed discussion of the results, implications for theory and practice, as well as, limitations and future work.

2 Literature Review

2.1 Personalized Learning

2.1.1 Moving towards Personalized Learning

Over the past decades learning has faced a fundamental shift from teacher-centered learning towards learner-centric models of learning. The main reason is that vision of learning has been re-identified as personal and social and learning has expanded beyond formal settings [10]. Learning is considered personal. “Learning is self-directed... The Learner may not have control over what is taught but the learner always has control over what is learned” [63] (p.vii). Also learning is inherently social [10]. Recent advancement in the web technologies has provided solid grounds for operationalizing social networked learning. New generations of learners are not only consumers of knowledge but also active producers. In addition, learning is not anymore restricted to boundaries of formal learning in academic institutions. It can occur throughout lifetime in both formal and informal settings such as work, play and home.

Personalized Learning has emerged as a new venue in Technology-Enhanced Learning to overcome the limitations of the traditional solutions and adapt to the newly raised notion of learning. Traditional approaches to Technology-Enhanced Learning follow static and fixed approaches to design and delivery of learning content through centralized Virtual Learning Environments. This one-size-fit approach doesn’t always lead to improvements of academic achievement and better learning outcomes as they suffer from the capability to meet the need of the diverse range of students [10]. Providing learners with access to wide range of tools to choose from and adapt the learning environments based on individual needs are among directions taken towards personalized Learning.

2.1.2 Aptitudes, Motivational Constructs and Achievement Goal Orientations

Personalized Learning relies on different treatments for individuals. Therefore we need to consider theoretical constructs that light up on personal characteristics of the

learners in a particular educational context [65]. Such theoretical constructs or so called aptitudes are [61]:

> "…individuals differ in their readiness to profit from a particular treatment at a particular time; aptitude constructs are theoretical concepts fashioned to interpret these observed differences in person–situation interaction terms. An aptitude, then, is a complex of personal characteristics identified before and during treatment that accounts for a person's end state after a particular treatment." [61] (p.205)

Accordingly, these aptitude constructs are the underlying reasons for observed differences between individuals in a particular context and cover a wide domain including motivational constructs (e.g., achievement goals [17]), beliefs (e.g., epistemic beliefs [7]), styles (e.g., study approaches [5]) and attitudes (e.g., perceived abilities).

> "…the domain of aptitude is not limited to intelligence or some fixed list of differential abilities but includes personality and motivational differences along with styles, attitudes, and beliefs as well. Also, no particular theory or measurement model for personality or ability is implied. "[61] (p.205)

Among all aptitudes, motivation remains as an important and yet complex personal factor that influences learning. Particularly, it is highlighted that "The real obstacle in education remains student motivation. Especially in an age of informational abundance, getting access to knowledge isn't the bottleneck, mustering the will to master it is." [3]

One of the most prominent theories of motivation in educational research is Achievement Goal Orientation (AGO) theory which describes "the purpose of engaging in an achievement behavior" [16] (p.632). In the early definitions, two main goal orientations were identified: mastery goal orientation which was conceptualized in terms of development of task competence and performance goal orientation which was conceived as the illustration of performance competence. In terms of valence, these achievement goals were further distinguished by approaching success and avoiding failure in a certain competence [18, 19]. In that sense, an individual with mastery-approach goal strives to

[3] http://chronicle.com/article/Why-Technology-Will-Never-Fix/230185/

do well on the task while an individual with mastery-avoidance goal strives to avoid doing poorly on the task.

Recent research has emphasized that the term “purpose” in the definition of Achievement Goal has two related and yet different aspects that needs to be distinguished: the aim pursued while engaging in an achievement behavior (competence types) and the underlying reason for such engagement (developing or illustrating competence) [16]. Therefore, achievement has been precisely redefined as the aim of engagement in an achievement behavior [16]. In this sense, competence is described as the standard used in evaluation of how well one is doing. Three main evaluative reference points are task, self, and other [16]. This shows a shift from models focused on development versus illustration of competence to models that focus on different standards for competence evaluation. Task-based goals use absolute standards for the evaluation reference and define competence based on doing well or poorly relative to the requirements of the task. Self-based goals adopt intrapersonal standards and define competence in terms of doing well or poorly with respect to how one has done before or can potentially do in the future. Other-based goals rely on interpersonal standards and define competence based on doing well or poorly compared to others.

Task-based and self-based goals are intertwined as they are both based on private standards, and yet they are not close enough to be considered in the same category as they were in Mastery goals in prior models. Other-based goals are similar to Performance goals in earlier models. However, with the standard-based definition of achievement goals they are considered as normative comparison for development of competence rather than illustration of such competence. Using task-based standards is more straightforward and smoothly aligned with the process of doing the task [16]. Therefore, it is optimal for the process of regulating learning. However, self-based goals demand higher cognitive load as they require comparison between the current outcome and the outcome of another time, which is not currently present. While these standards can be useful for calibration of self-perception it makes the regulation process less smooth and rises up new concerns of self-esteem. Other-based standards use interpersonal measures for evaluation [16]. In some cases the norm is more concrete and explicitly available such as in competitions. In this case it requires only slightly more cognitive processing than task-based goals but

when it is implicit it can be as complex as self-based measures. Although not ideal, it can be effective towards task management

2.2 Learning Analytics Visualizations and Dashboards for Learners

2.2.1 Learning Analytics

Learning Analytics is considered a newly emerged area in Technology-Enhanced Learning research that draws on methods and techniques from diverse range of research fields including educational psychology, learning sciences, technology and information visualization [20, 27]. As defined in the first Learning Analytics and Knowledge Conference back in 2011[4], learning analytics is the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environment in which it occurs". Learning Analytics is different from similar research communities (e.g, Educational Data Mining) as it is more interested in human-led methods and techniques for exploring educational data rather than development of automated methods and sophisticated models [4]. Hence, Learning Analytics takes holistic approach to understanding and interpreting phenomena hidden underneath educational data [4].

Learning analytics was initially focused on institutions to inform educators including administrators, program coordinators, course designers, and instructors about students' engagement and academic performance, and to support their decision making to maintain students' retention. However, recently Learning Analytics have been realized as a particularly powerful (and yet challenging) opportunity to focus on learners perspective and put these new learning tools in the hands of students to support their development as intentional, self-regulated learners [53]. This can help address the long-known problems of students not consistently receiving relevant, timely and personalized feedback on their learning and as a consequence not engaging as active drivers and monitors of their own

[4] https://tekri.athabascau.ca/analytics/

learning. Learning Analytics also allows for expanding the measures of success beyond academic achievement to consider satisfaction, enjoyment and mostly motivation of learners [20]. One way of providing feedback to students through Learning Analytics is in the form of visualizations and dashboards.

2.2.2 Review of Learning Analytics Visualizations and Dashboards for Learners

A wide range of dashboards have been designed, developed, and evaluated that track learners' activities in online learning environments and present them in the form of visualizations or dashboards [64]. While many of the existing dashboards are targeted just at instructors very few are intended for students. Such dashboards are presented to students so they can monitor and manage their own learning. Research on Learning Analytics tools suggests that reporting and visualizing analytics that are personalized and are easy to understand for the learners and have clear connections with improving their learning processes and outcomes can be very helpful [20].

These dashboards differ in terms of the type of data, the visual representation used to present data and their evaluation. Some dashboards provide overview of all activities in the learning environment, while others are focused at specific learning activities. Several of these dashboards that can be used by learners are presented here:

Student Activity Meter (SAM) [28] is a learning dashboard that tracks the time spent on learning activities (average and total) and frequency of access to resources from a learning environment including a Learning Management System such as Moodle. SAM uses bar charts, line charts and parallel coordinates to represent the time spent (Figure 2-1). It is available to students and teachers both on web and as a desktop application. Following a design-based research methodology, the dashboard went through 4 iterations of rapid prototyping and was evaluated over a period of 24 months with a series of surveys and interviews. The initial stage involved usability and usefulness evaluation by students in an HCI course using a standard SUS questionnaire. Similar evaluations were conducted by the teachers from various disciplines using existing data captured from science courses, as well as, experts in the field of Learning Analytics. Feedback from these 3 iterations led to implementation of a search and filtering capability, which was again evaluated by teachers in terms of perceived usefulness.

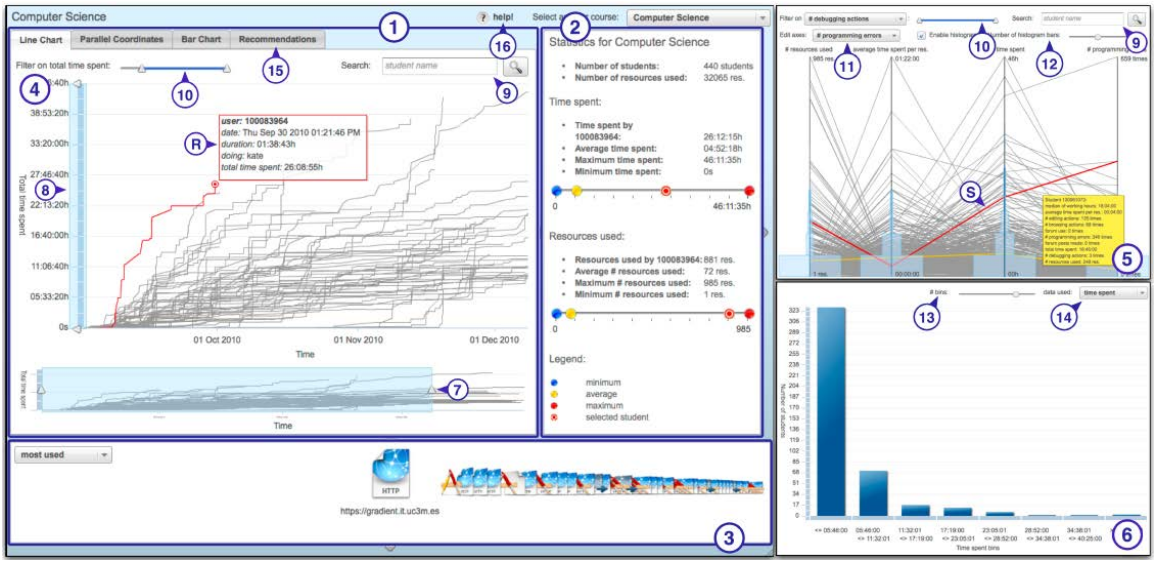

Figure 2-1: Student Activity Meter (SAM) Visualization [28]

Authors of [56] take a goal-oriented approach to visualization with the incentive to increase learners' motivation and self-reflection. They use a mash up visualization that focus on tracking data from several applications (e.g., a programming IDE, websites, etc.) and comparing it with their peer. They present information about students' goal in the course and their learning activities with respect to those goals. It demonstrates student's goal status (in progress, achieved, failed), quantity of goals approached overtime, and timeline of activities performed or documents accessed to achieve a goal (Figure 2-2).

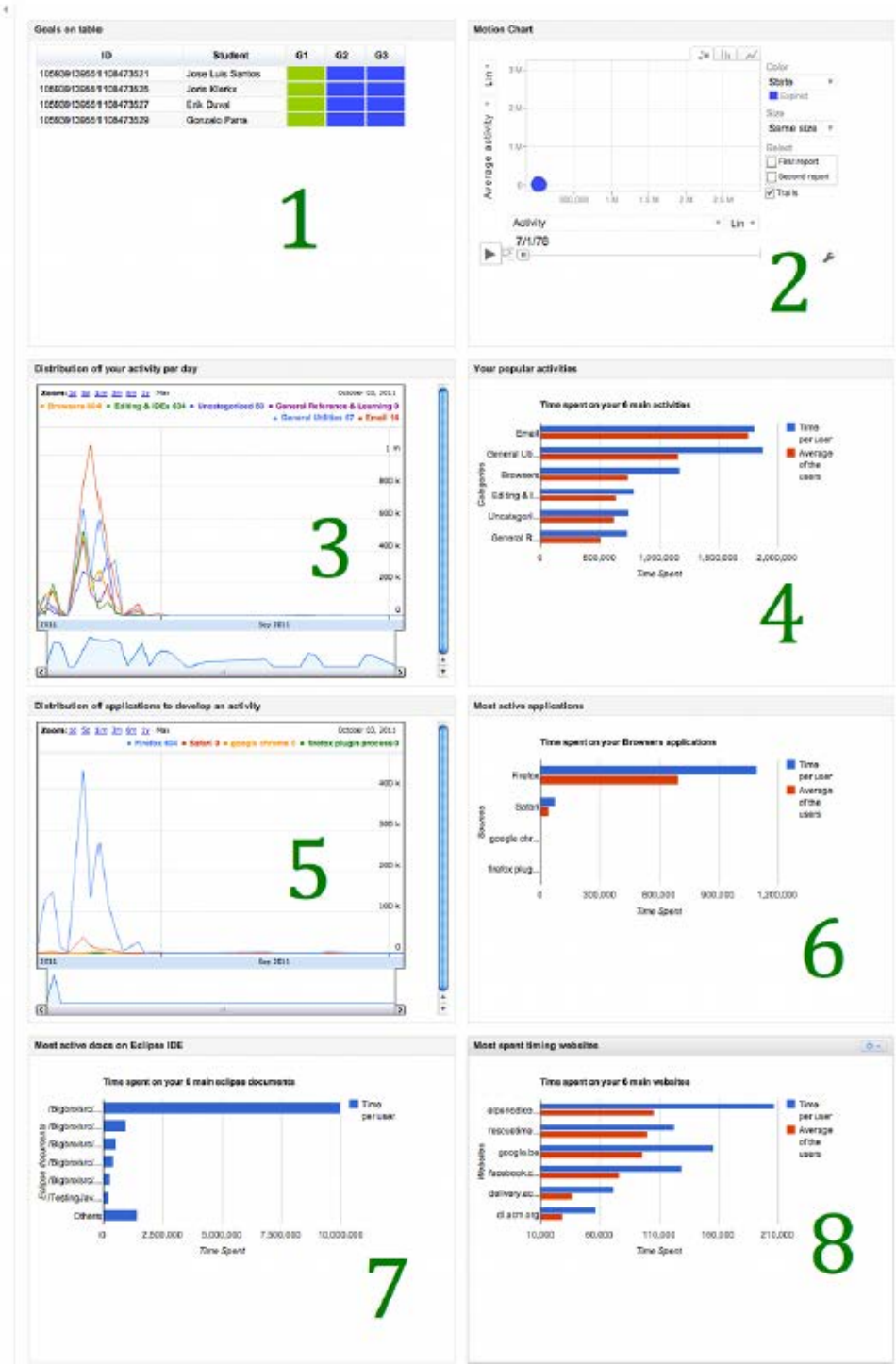

Figure 2-2: Goal-Oriented Visualization [56]

Also students can publicly or privately communicate about their goals with peers and teachers. Using design-based research they initially evaluated a paper-prototype with

6 people who were asked to perform predefined task for 30 minutes and later were interviewed. After minor modifications, a digital prototype was made and similar evaluation was conducted with fake data. Finally, a working prototype was implemented and was evaluated with 36 students in an undergraduate engineering course. Data of two users was used as an input and presented to all students using tables, motion bubble charts, line and bar chart. Using survey students reported on perceived usefulness, usability, satisfaction and privacy concerns and general positive and negative feedback. Later, the modified dashboard was evaluated with 10 students in the lab setting across four sessions. In the sessions, participants actually used the dashboard to carry out several tasks. The standard SUS questionnaire was used for usability evaluation.

QuizMap [8] focuses on showing students' progress in self-assessment quizzes with respect to their peers in a group or a larger class. It uses a hierarchical treemap visualization that presents performance measures in terms of the amount of work done (number of attempts to take the assessment) and knowledge gained (success rate) at four levels (from general to specific: class, topic, quiz and individual learner) (Figure 2-3). Evaluations were conducted in a classroom setting with 86 undergraduate students in a second level programming course. The results show that students who actively used QuizMap explored more topics but had lower success rate than less frequent users. However, their learning gain in terms of size of the success rate increase after using QuizMap was higher. Also a standard survey was used to evaluate usefulness, ease of learning, and ease of use, privacy and satisfaction with the system.

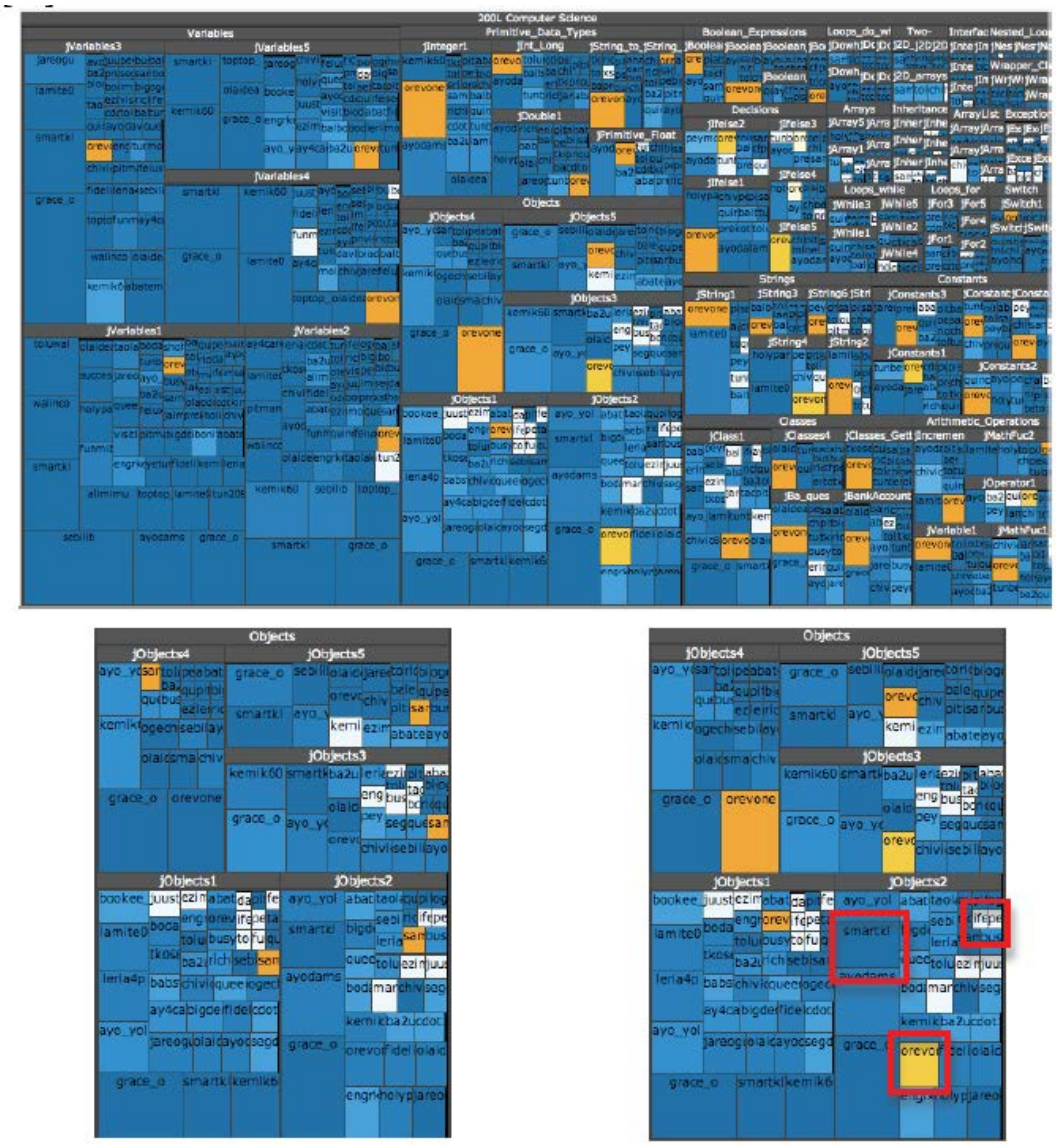

Figure 2-3: QuizMap Visualization [8]

In [46] authors used eye gaze tracking method to investigate how students use the provided visualization. They tested four different representations (kiviat chart, tag cloud, concept hierarchy and treemap) with 17 participants from second year undergraduate students in a database course (Figure 2-4). In an hour lab setting participants were asked to use these visualizations for several problem-solving questions focusing on understanding the visualizations. Through surveys participants also reported their

understanding of the visualizations. The scores from survey and their eye gaze data was used to compute the efficiency of each visualization. Analysis showed that students were more efficient with kiviat and concept hierarchy. They experienced difficulties using the other two visualizations which was also confirmed by survey results. This suggests that eye tracking method has the potential for understanding students' use of visual analytics.

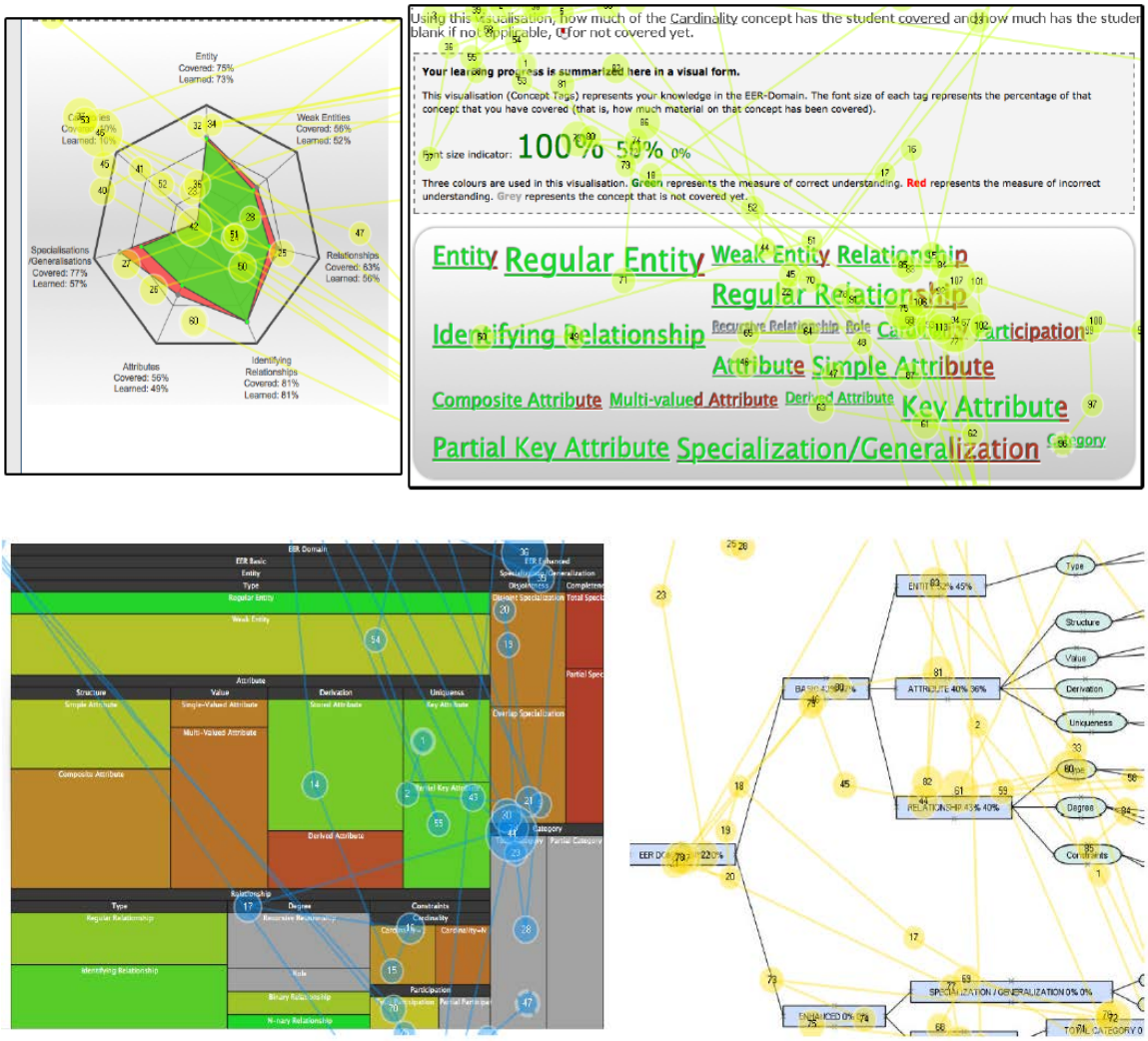

Figure 2-4: Gazeplot for Visualization [46]

Course Signals [3] uses Learning Analytics to provide feedback to students. It predicts students risk level using several sources of data including their performance in the course, their engagement in terms of interaction with the Learning Management

System, their academic history (e.g, GPA and background) and demographics (e.g, age and residency). The output is represented using a traffic light that shows three risk levels, high (red), medium (yellow) and low (green) and is sent to students through several communication channels (email, text, LMS). Course Signals was evaluated at large scale with over 24,000 student users showing improvements in academic achievement (i.e., students' final course grade). Also their findings show that using Course Signals has positive association with students' retention rates. According to survey results, both instructors and students have positive impressions about this tool.

A competency map is used in [33] to visualize students' status on a particular competence at the course level. Competencies are described as skills required to successfully perform a task in a given context. This type of visualization is suited for institutions where programs are designed around accomplishment of certain competencies and that instructor's grading is strictly aligned with achievement of those competencies. They used colored circles where the shade shows the percentage of criteria met to accomplish a competency and color of the circle shows the performance on a competency based on history of grades on all components related to that competency (Figure 2-5). This visualization was evaluated in a graduate MBA course. Analysis showed that students who used competency map had slightly higher academic performance in terms of level of competency. Also their level of usage of the visualization positively predicted their retention in the program.

Figure 2-5: Competency Map Visualization [33]

Gradient's Learning Analytics System (Glass) [43] proposes a layered architecture to support modular visualizations that can gather data from multiple learning platforms. The data layer consists of two types of databases; one for the learning platform configurations and the other to store tracked data for visualization on that platform. The code layer does the core functionality while module layer has a set of modules for generation and setting configurations of the visualization (e.g., filtering). Finally, the last layer is the actual visualization. Authors implemented a sample visualization using this architecture that shows frequency of activities over time and for different groups of learners. However, no evaluation is conducted on the proposed architecture (Figure 2-6).

Figure 2-6: Gradient's Learning Analytics System (Glass) Visualization [43]

StepUp! [55] is a learning analytics visualization that aims at empowering learners to reflect on their learning. Through brain storming sessions in 3 different graduate level

courses, students were asked to report and rate their issues in studying. Most reported issues that could potentially be solved using StepUp! were selected and minor revisions were applied. Each row in the final dashboard corresponds to a student in the class, columns show number of comments students posted in their group blog or other groups' blog (Figure 2-7). Also their total number of comments and tweets and the total time spent on the course is displayed in the last columns. A Sparkline shows activities over time with more details displayed on frequency and time spent on activities over weeks in the course. Students were asked to fill couple of surveys to re-rate issues, self-assess how step-up helped solve those issues and standard usability questionnaire (SUS). The evaluations over six-week period show that students in different courses had different rating of issues. Student reported that the dashboard helped them understand and communicate better with their peers. However, they don't think that visualization increased their motivation or decreased their workload. Overall, students in courses which required more group work found this tool to be more useful.

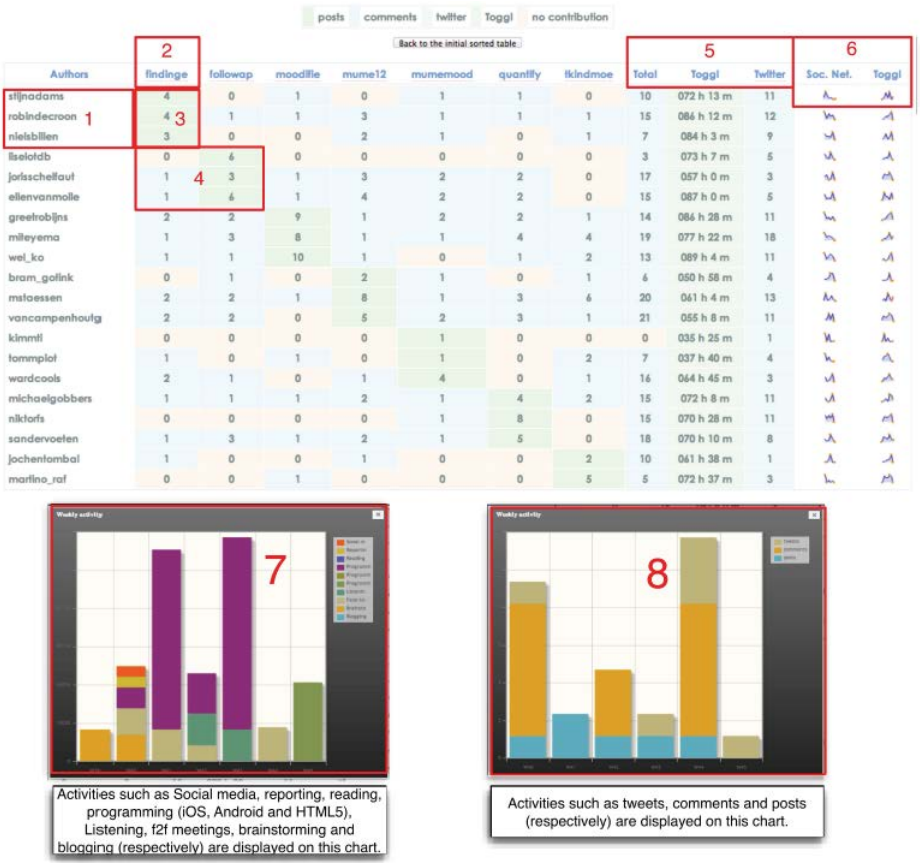

Figure 2-7: StepUp! Visualization [55]

Learning Analytics Reflection & Awareness environment (LARAe) [9] is an offline dashboard with the aim to raise awareness about active individuals and groups and the content generated by them. It shows history of students' activities (e.g, blogs, tweets and comments) categorized by type and student groups (Figure 2-8). Each activity is represented using a circle, which is linked to the relevant content. Also, order of the circles shows their temporal precedence. This dashboard has not been evaluated.

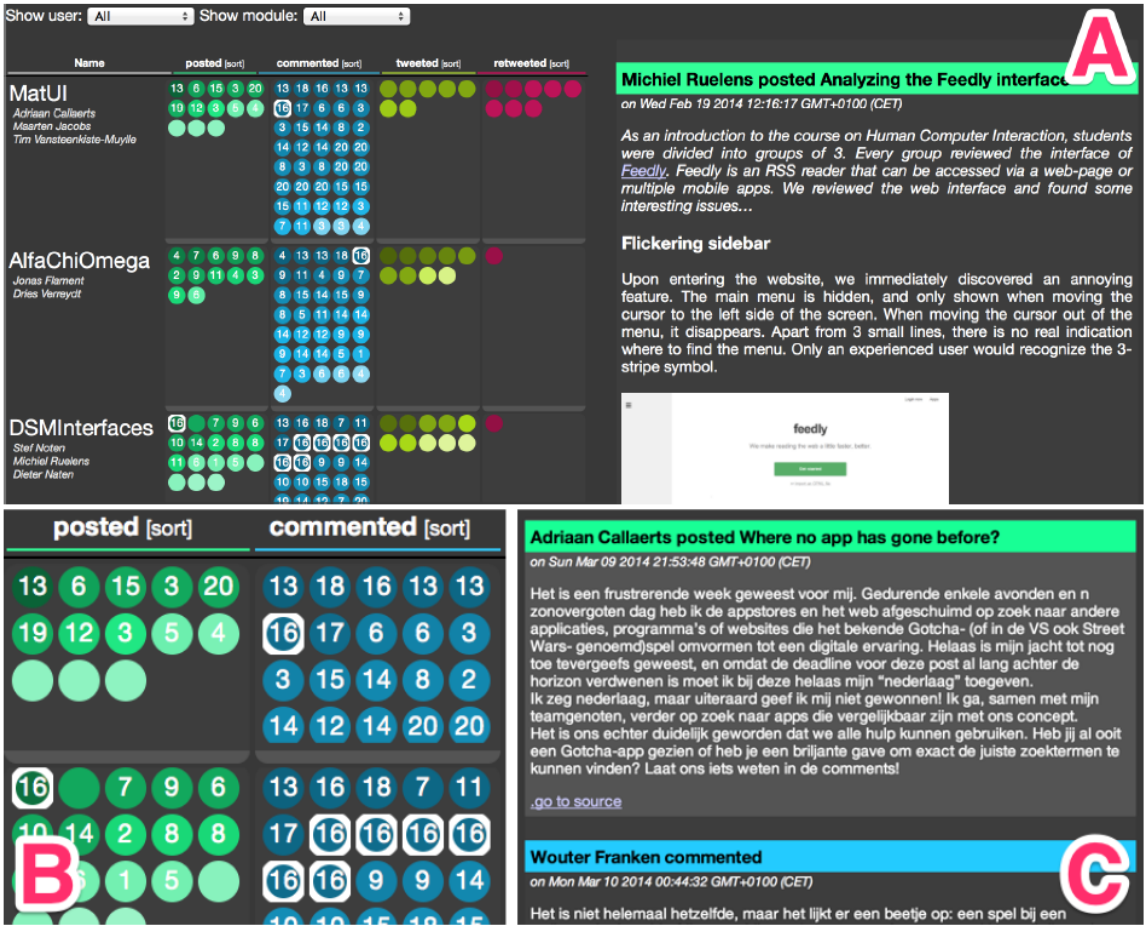

Figure 2-8: Learning Analytics Reflection & Awareness environment (LARAe) [9]

2.2.3 Limitations of Existing Learning Analytics Dashboards for Learners

Review of existing Learning Analytics dashboards and visualizations for learners (Section 2.2.2) reveals several limitations:

Designs are not Theoretically Informed. Many of the existing Learning Analytics dashboards primarily focus on theories and practices of information and data visualization which is concerned with type of visual representations (e.g., bar charts. Spark lines, treemap, concept tag) and interaction techniques (e.g., overview-zoom-filter and focus context techniques) [46]. While these are important guidelines from usability perspective, Learning Analytics Visualization designs needs to be further informed by theories of learning sciences and educational psychology to encourage adoption of effective instructional and intervention practices, and thus afford an actual impact on learning. Currently there is a gap between involved fields i.e., Information visualization and learning sciences. Without careful considerations, the design of dashboards can result in implementation of fragile and undesirable instructional practices by promoting ineffective feedback types and methods [27]. To address this problem, it is vital for Learning Analytics researchers to draw on existing educational research and theory as they develop their applications and dashboards [66].

Evaluation are not focused on the learning impact. In terms of evaluation, many of these dashboards have remained unevaluated [9, 43]. Those with evaluations mostly focus on assessing usability using standard or open-ended questionnaires and interviews. While usability is relatively easy to measure and can provide valuable insight on learners' experience with these visualizations, it is not revealing of the affordances of such tools when it comes to actual impact on learning. Hence, few of the existing studies, ask students to report the perceived usefulness of the designed tool on their learning experience. There are two problems associated with this method. First, research shows that student don't necessarily have accurate perception about their learning [64]. Second, many of such tools are mainly at the stage of low fidelity mockups or working prototypes. Therefore, students are unable to use them in real course settings to have a clear judgment of the effectiveness of the tool on their learning.

There is limited empirical research to date that have sought to evaluate the impact of such Learning Analytics tools and dashboards. Particularly, very few studies focus on evaluating the actual effectiveness of fully implemented dashboards on students' learning [3, 8, 39, 50]. The impact in these studies is measured in terms of engagement [50], progress [8], academic achievement [3] and retention rates [3]. Out of these few, most are small-scale studies that rely on controlled experiments in lab settings isolated from an

actual learning context [8, 39, 50]. Course Signal is the only dashboard that has been evaluated at larger scale in authentic course settings over a long period of time and shows significant benefit on the retention of learners and their academic achievement [3]. To improve design of dashboards in accordance with practices of educational psychology, more large scale empirical studies are required to assess the effectiveness and re-structure design principles [40, 64].

Analytics are focused on quantity rather than quality. In terms of the type of data tracked and presented, many of these visualization present raw data on frequency and timing of learners' activities (interactions), artifacts produced or resources accessed. In the process of managing one's own learning, quality of produced artifacts or interaction are equally important as is the frequency and time of interactions {Citation}. However, to date less attention has been paid to providing feedback to learners on their quality of learning interaction and products from raw logged data. Using natural language processing techniques to carry out content and discourse analysis on the textual content generated by the students is a promising research direction [47].

Learners' aptitudes are not considered. In addition, a review of research on learning analytics tools and visualizations to date illuminates that current focus hugely falls on the information that can be extracted from the log data rather than how individual differences might affect interpretation of the information presented to the learner in terms of reflection and taking actions [27]. As explained in Section 2.1.1, research shows that aptitude constructs (e.g., achievement goals [17], epistemic beliefs [7], study approaches [5] and attitudes) are the underlying reasons for observed differences between individuals in a particular context. When it is comes to learning analytics visualizations such constructs may play a role on how individual students interpret the analytics visualizations (reflect on how they are doing) and how those visualizations affect their learning (impact).

For instance, a common method used for reporting analytics is to show a comparison between the learner and the class average on a particular measure. A study shows that for students who had high achievement goals, seeing class average led them to misinterpret that they were doing well because of being slightly above the average [11]. Findings of another study revealed that showing class average in online discussions resulted in mixed responses based on learner's interpretation. While some students find it motivating and useful, others felt it was stressful [66]. Also many of these tools enable

learners to compare and contrast their data with peers. It is commonly hypothesized that such visualizations have negative effects on learners with low levels of self-efficacy [27]. Therefore, understanding how different learners interact with different Learning Analytics Visualizations can help inform their design in the future. This is aligned with the goals of Personalized Learning Environments towards fostering a more personalized learning experience.

As this overview shows, while Learning Analytics visualization holds clear potential benefit for learners, these potentials cannot not live up to their promises if design of Learning Analytics tools and visualizations are not informed by theories of learning sciences and practices of instructional strategies. Hence, further empirical studies are needed to investigate the actual impact of these visualizations on learning processes and inform future designs. In that line, it is crucial to consider the aptitude constructs as basis of how individuals interact and interpret the Learning Analytics Visualizations and what is the effect on their learning processes and outcomes [11].

2.3 Learning Analytics for Online Discussions

From a social constructivist perspective, online discussions can be seen as an environment in which learners can interact to build both collective and individual understanding through conversation with one another. It presents learners with the opportunity to discuss and compare ideas with others, construct knowledge as a group [38], as well as, reflect on their critical thinking [34] and revisit their own ideas. Asynchronous online discussions are commonly exploited to support collaborative learning in distant and blended courses particularly at higher education level [2, 44]. In this type of online discussions learners have greater control over the pace of their engagement [37]. While this creates an opportunity for productive participation through thoughtful reading of other's posts and contributions, it also brings challenges of time management [51]. Hence, online discussions don't always live up to their promises as they usually suffer from participation issues. Lack of discussion depth [49] and interaction quality [62], free riding behaviors [57], bias to new posts [67], large number of messages to read, unequal participation (dominancy by a small group), misunderstanding and lack of motivation [45] are among the reported issues. For this reason, providing learners with analytics

dashboards to monitor their participation in online discussions can be supportive of productive engagement in discussions.

Recent research has revealed that learners with individual differences exhibit different behaviors when engaging in online discussions [69, 71, 73]. For instance, a study [69] shows 3 different patterns of participation on online discussions with regards to Achievement Goal Orientations. Learners with performance avoidance goal-orientation had minimal engagement in online discussions. Broad participant who invested a lot of time and covered many of their peers post were associated with mastery goal orientation. Concentrated participants who had limited but long learning sessions were considered task-focused. Except for the first group that don't seem to be effectively engaged in online discussions, the pattern of the other two groups suggest that student have different participation behaviors in online discussion that are not necessarily preferable over each other. Hence, they may require different support [69].

Prior research shows that providing Learning Analytics in online discussions can be useful for both individual and collective learning if accompanied with a properly designed pedagogical intervention to support their use [70]. A recent study [66], suggests using two classes of Learning Analytics for online discussions: embedded and extracted. According to their definition, embedded analytics are integrated into the discussion environment to provide real-time feedback to students that could guide them as they are participating. On the other hand, extracted analytics are captured periodically and presented after participating in the discussion as a separate exercise. While embedded analytics have the benefit of being used seamlessly as a part of the discussion activity itself, they have the potentials to be ignore. Such extracted analytics can be presented in the form of report or visualizations. In their work, analytics are presented to students in the form of reports. However, it is suggested that visualizations and dashboards can also be used for this purpose.

Existing body of research suggests that using Learning Analytics in the form of dashboards or reports for online discussions can lead to change of behaviors that are sometimes intentional and goal-oriented and sometimes unconscious [66]. Nevertheless, similar to original pattern of engagement in online discussion, the direction of change resulted from access to a set of Learning Analytics measures about participation in

discussion can very among learners with individual differences. In [66], participants indicated that they find the provided analytics a good reference to compare with. However, their reference points varied. For some instructional guidelines served as the main reference, while other looked at their peers or how they had done in the past [66].

Despite the clear potential benefits that Learning Analytics Visualizations hold for learners in online discussions, limited endeavor has been directed at studying the effect of using Learning Analytics Visualizations on students' participation, and subsequently learning in online discussions. Particularly, the role that aptitudes including motivational constructs play on using these visualizations and their effect on the students' participation has been overlooked [11]. In particular with regards to achievement goal construct it is suggested that "More attention to students' goals for participating in online discussions is also warranted. Students who are oriented towards mastery and see discussions as vehicles to support this goal are likely to participate in productive ways. In contrast, for students oriented toward performance goals, explicitly embedding desirable participation behaviors in the activity requirements and assessment scheme can help encourage more productive listening and speaking." [69]. This suggests that students with different Achievement Goal Orientations may not benefit from Learning Analytics Visualizations intended for online discussions in the same manner.

3 Method

3.1 Experimental Design and Research Questions

To study the effects of Learning Analytics Visualizations on students' participation in online discussion, we conducted a controlled experiment where students in an authentic blended course setting were split into several groups and were asked to engage in an online group discussion task on a topic related to the course content (Section 3.3.2). Each student in the course was assigned to an experimental condition in which they had access to one of three visualizations designed to help them inform on how they are doing in the group discussion task. These visualizations will be explained in Section 3.2. This assignment to the conditions was random and computed using checksum on student ID.

To further investigate the contribution that individual difference (e.g., Achievement Goal Orientations) may play on their participation in the discussions when using different Learning Analytics Visualizations, students were invited to take part in the experiment by filling the questionnaires described in (Section 3.6.2). Therefore, Questionnaire responses were only available for volunteered participants which were a smaller subset of all students. Finally, the study was replicated over several discussion tasks in several courses (Section 3.4).

Accordingly, we aimed to find out if those who used the Learning Analytics Visualizations versus those who did not were associated with different posting behaviors and for those who used the Learning Analytics Visualizations their level of usage influenced their posting behavior. Also we aimed at finding out the effect of different visualizations on students' level of engagement with the Learning Analytics Visualizations and its influence on their posting behavior. Finally, we studied how considering self-reported Achievement Goal Orientations affected the association between different Learning Analytics Visualizations and the above dependent variables. We precisely defined our research questions as follows:

- RQ1: Is there an effect of the visualization type on the users' level of engagement with Learning Analytics Visualization?

    - RQ1.1: Is there an effect of visualization type on the users' level of engagement with Learning Analytics Visualizations when controlled for their self-reported Achievement Goal Orientations?

- RQ2: Is there an effect of using Learning Analytics Visualizations on the students' posting behavior? (quantity and quality of posts)

    - RQ2.1: For the users, is there an effect of level of using Learning Analytics Visualizations on the students' posting behavior? (quantity and quality of posts)

- RQ3: Is there an effect of visualization type on the users' posting behavior? (quantity and quality of posts)

    - RQ3.1: Is there an effect of visualization type on users' posting behavior when controlled for their self-reported Achievement Goal Orientations? (quantity and quality of posts)

3.2 Learning Analytics Visualizations

For the purpose of this study, three Learning Analytics Visualizations were designed that provide information about student's participation in online discussions. According to the random assignment explained in Section 3.1, only one out of the three visualization was available to each student in each discussion task. The structure of all the visualizations included several elements (Figure 3-1, Figure 3-2, and Figure 3-3).

At the top of each visualization, the topic of discussion associated with the visualization is displayed. Followed by that, there is a prompting question with the intention to trigger the reflective process for students when they view the visualization. From a constructivist viewpoint, reflection is an important aspect of constructing one's understanding and an important consideration when designing analytics dashboards [70]. Finally the core of visualization is illustrated which is composed of two parts. The first part present the analytics metric about the student who is viewing the visualization. While the other part, shows the same metric for the rest of the class at the level of aggregate or individuals. This can provide a means for the student to compare themselves with their peers. At the bottom of the visualization, there is an information button that serves as a guideline for students [72]. Once the student clicks on that button they can see a

description about the visualization and the importance of the metrics presented. Also the last update time of the visualization is recorded.

The designed visualizations were integrated as an external tool into the Learning Management System (LMS) used in the courses[5] in accordance to Learning Tools Interoperability (LTI) standards[6]. A web application was developed which used Python and Java in the back-end to connect to LMS's REST API and get data from the discussions, compute the analytic metrics from the extracted data and store them in MongoDB. Also PHP was used to fetch the computed metrics from MongoDB. In the front end D3.js, which is a JavaScript library was used for visualization. The visualizations were updated every 5-10 minutes.

A description of each visualizations is presented in Section 3.2.1 to 3.2.3.

3.2.1 Class Average Visualization

This visualization shows the count of messages posted by the student in comparison to the average number of messages posted by the rest of the class in a particular discussion (Figure 3-1). Comparison of the students with the class average has been the most widely used approach when offering Learning Analytics dashboards and visualizations [11]. However, some prior research show that class average comparison is not necessarily associated with positive changes in students' participation and learning [11, 66]. Particularly, students whose overall goal were high achievement, seeing class average led them to misinterpret that they were doing well because of being slightly above the average [11]. Also some students have reported that the class average comparison increased their stress level [66]. We expect that this visualization would be less successful in promoting positive changes on students' participation compared to the other two visualizations. However, we are including because it is commonly used in the existing systems.

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[5] Canvas LMS (http://www.canvaslms.com/higher-education/)

[6] http://www.imsglobal.org/toolsinteroperability2.cfm

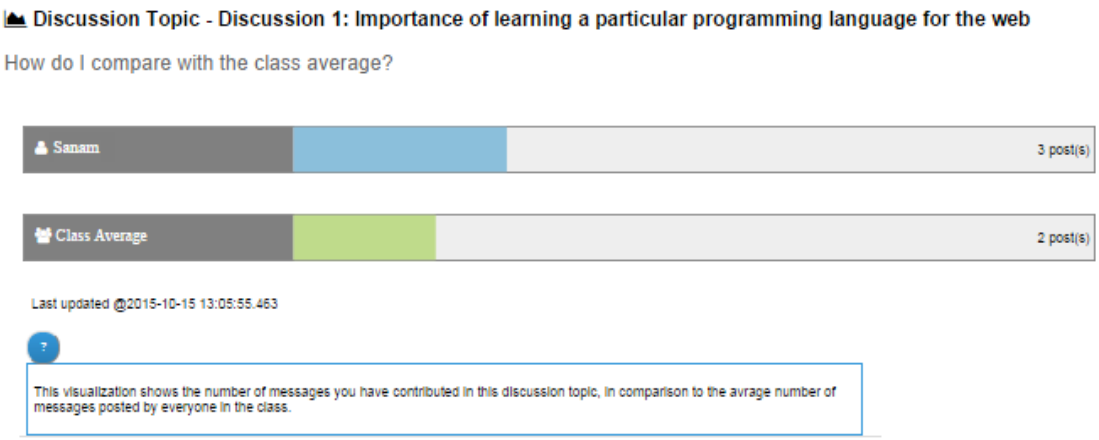

Figure 3-1: Class Average Visualization

3.2.2 Top Contributors Visualization

This visualization shows the count of posted messages by the student in comparison to the top contributors in the class (Figure 3-2). Top contributors are the top 5 individuals in the class who have had the highest number of messages posted to a particular discussion in descending order. The visualization starts showing students after they posted at least 2 messages. To have top contributors gain better recognition, their names and their LMS profile pictures is also included next to their contribution level.

We expect that this visualization would motivate students with other-approach goals to increase their contribution levels in the discussions. According to literature, individuals with other-approach goal strivings assess their competence level in terms of normative standards and aim at outperforming their peers [16]. In light of such visualization, they may interpret the norm based on the contribution level of those who had the highest number of postings in the class. Also they may strive to gain visibility by the rest of the class, which means being listed as top contributors themselves. Hence, this may motivate them to increase their participation by posting more.

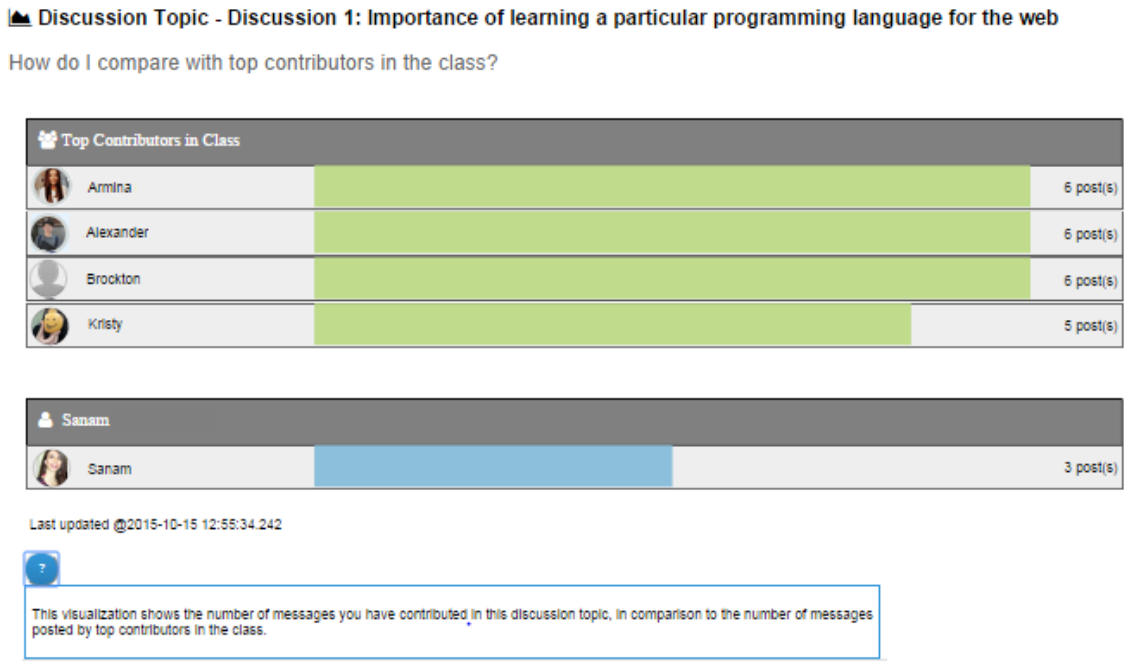

Figure 3-2: Top Contributors Visualization

3.2.3 Quality Visualization

Quality visualization focuses on the key concepts related to the topic of discussion. It represents how many of the key concepts the student has covered within his posted messages and how well he has integrated that with logically related ideas. It also shows the concepts covered by the rest of the class and how well others have integrated those concepts within their posts (Figure 3-3). The linguistic metric of coherence of the messages was used as a way to measure quality of such integration.

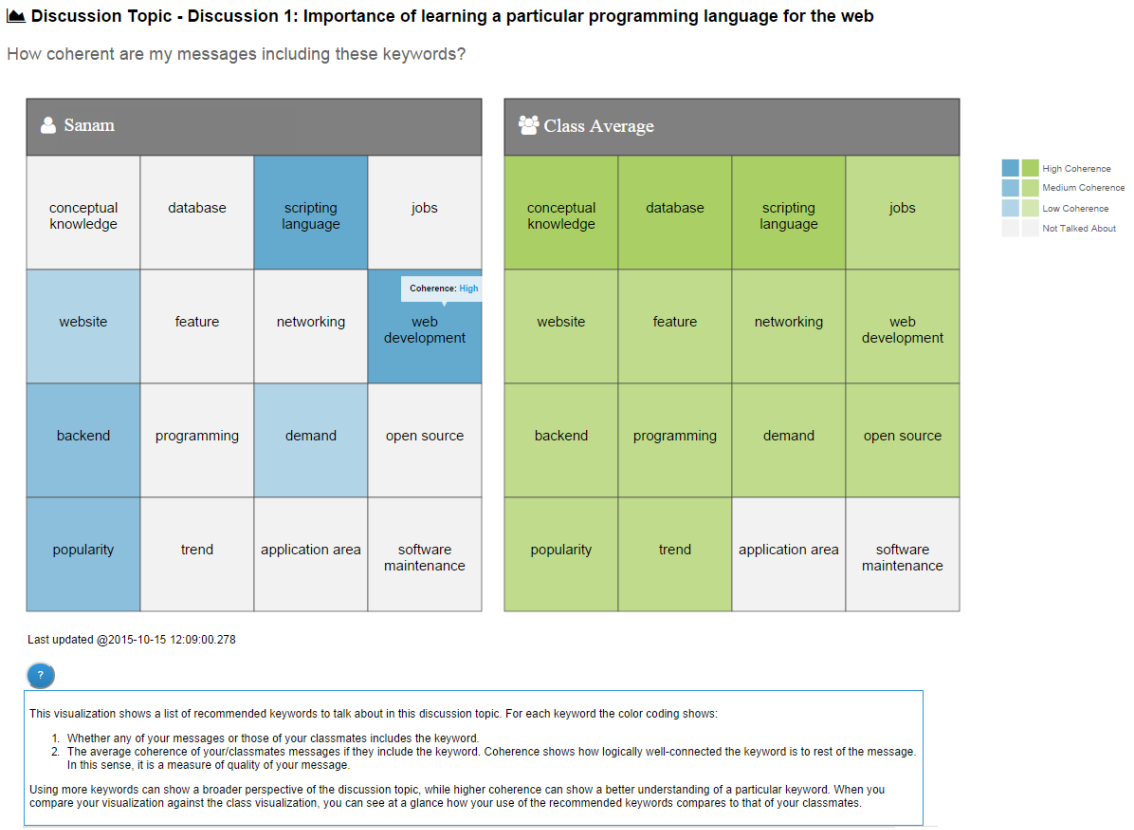

Figure 3-3: Quality Visualization

Coherence has been described as “the unifying element of good writing”[7] and hence it can be used in a way to measure quality of text. A coherent text reveals use of different strategies to connect and integrate disparate pieces of information together and to prior knowledge [21]. We adopt Latent Semantic Analysis (LSA), a natural language processing technique for measuring the coherence of the text. LSA algorithms compare two adjacent units of text at the semantic level to evaluate their relatedness [22]. Since in the discussion boards messages are mostly composed of several sentences, computation was performed at the granularity level of sentences. Also research shows that sentence is a preferable unit as it is almost aligned with the volume of information that can be stored in the short term memory [22].

[7] http://www.elc.polyu.edu.hk/elsc/material/Writing/coherenc.htm

The output value of LSA for coherence theoretically ranges between 0 to 1. Higher values shows higher semantic similarity between the sentences, and thus a more coherent message while smaller values indicate low semantic similarity and incoherent messages. In this visualization we use color coding to represent coherence at three levels: low, medium and high rather than the raw value. The darker shades of a concept indicate that the average coherence of the messages where this concept is mentioned (by the student or others in the class) is high, as opposed to low and medium.

To determine the thresholds for coherence levels (low, medium and high), we used an existing corpus of messages that had been pre-coded based on Cognitive Presence using the coding instrument described in [25]. Cognitive presence, coming from critical thinking literature, refers to the ability of the students to build meaning about the domain of study [25]. It has four stages: 1- Triggering Events, 2- Exploration, 3- Integration, and 4- Resolution. Students normally start at the lowest stage and gradually progress to higher stages. However, not all the students manage to develop their critical thinking to the last stage. The corpus used for analysis included 1,747 messages from the online discussions in 6 offerings of a Master's level Software Engineering course. This fully online course was offered in a Canadian public university. Coding was conducted by two human coders and they achieved an excellent agreement (Cohen's Kappa=0.97).

We computed 9 different sentence-to-sentence similarity measures from LSA on the messages in this corpus. For 6 out of 9 measures, statistical significant difference was observed between the LSA measures for messages coded at different cognitive presence levels. For all the 6 measures, we followed up with pairwise comparison also using Benferroni correction and selected the measure that had the most distinguishing power. Accordingly, we selected Lexical Overlap Comparer. This measure relies on the number of words that overlap between two sentences. The Kruskal-Wallis test revealed significant difference between the values by Lexical Overlap Comparer for messages with different cognitive presence codings ($H(4)=131.85$, $p<0.001$). Also post-hoc analysis further revealed significant difference between messages coded at all stages except for stage 0-1 and stage 3- 4. Hence, we decided that low level on the quality of the messages would correspond to stage 0 and 1 of cognitive presence, medium quality to stage 2 and high quality to stage 3 and 4. We used the median value of lexical overlap comparer for messages coded at stage 3 and 4 as the minimum threshold for high coherence (0.201).

Also the median value for messages coded at level 2 was selected as the minimum threshold for medium coherence (0.101).

We expect that this visualization would motivate students with task-approach goals to increase the quality of their contributions. Research shows that students with task-approach tendency perceive the task as valuable and use deep learning strategies to master the task by following the requirements of the task [58]. This visualization my help them construct messages in accordance with concepts related to the topic of discussion task and integrate them with logically related ideas and background knowledge. Hence, it can help them construct messages that show signs of higher quality.

3.3 Online Group Discussion Task

3.3.1 General Guidelines on Discussion Design and Facilitation

For students to engage in productive discussion and knowledge construction in an effective social constructivist environment, the discussion activity has to be properly designed. We adopted guidelines on design and facilitation of effective discussions based on the dimensions suggested in collaborative learning literature [54, 76]:

- *Motivation:* Use grading strategies to influence students' extrinsic motivation to participate in discussions. The suggested weight is 10-20% towards the final grade.

- *Task-oriented:* Associate discussions to another course component to maintain task-orientation and relevance to the course content. This can increase students' intrinsic motivation and enable them to construct knowledge in practical ways.

- *Participation expectations:* Provide students with a participation rubric to communicate the expectations and standards regarding interactions in online discussions. Rubric needs to cover different aspect including quantity, quality (content), tone, mechanics and collaboration *[54]* , as well as, timing of the postings *[74]*

- *Group structure:* Limit group discussions to at least 10 students and at most 20-30 students to avoid too less and too many interactions.

- *Student-centered:* Try to avoid teacher-centered discussions and focus on creating a space for student-student dialogue.

- *Discussion Topics:* Efficient discussion requires good choice of discussion topics that are open-ended. Topics that can reflect on students' learning may include summaries, most important point, muddiest point, decision making based on advantages and disadvantages and debates.

- *Role Assignment:* Assign roles to students in a group and rotate the role between group members across multiple discussions to promote equal participation. Role assignment is a scripting method that can be used to give students guidance on particular engagement approach in discussions. These roles can include starter, source searcher, synthesizer, wrapper (summarizer), moderator, and presenter *[12, 26, 74]*. We suggested use of two roles, wrapper and presenter. The wrapper is responsible for summarizing ideas introduced by others and posting a final response on behalf of the group. A presenter will be representing the group in the class. The presenter will be asked to either participate in a debate where he will be assigned to argue for the position that is not consistent with his group's conclusion or just present the final response of the group. Recent studies shows positive effect of role assignment on collective knowledge construction and individual cognitive presence level *[12, 26]*, particularly summarizing roles like wrapper can increase broadness of attention to others posts *[74]*.

3.3.2 Discussion Task Description

For the online group discussion task, the students were split into several groups of 4-11 members and were asked to participate in an online group discussion task over a period of 7-14 days.

All the groups in a particular discussion were given the same set of open-ended questions related to the course content and were expected to engage in the discussion by exploring different aspects of the question itself, proposing different ideas to address them, selecting some ideas and finally deciding on one answer as a group and justifying it with a clear rationale. Examples of questions used in this experiment are:

- "In this course, it is/it is not important that students learn how to program web applications in the programming/scripting language X." Discuss and come up with pros and cons arguments for the statement. Support with facts/sources. Discuss what X should be, and why.
- "What new challenges and opportunities the big data phenomenon brings as compared to database systems of yesterday?" Discuss all possible angles of the topic ranging from technical and management issues, through societal, policy-making aspects to personal (and anything else you identify). Support with facts/sources.
- "Cloud computing is one of the new buzzwords in the internet computing community. Is it just a new name for the old set of technologies, or does it represent

a significant breakthrough that takes computing to the new level? ”Discuss and come to conclusion. Support with facts/sources.

The final response for the group had to be posted by one of the group members (wrapper role). Furthermore, another group member had to present the group’s response in front of the class or participate in a class debate (presenter role) (Figure 3-4)

Engagement in the discussion was mandatory and was considered a graded component of the course (5% of final grade per discussion task). Marking rubric was also provided which thoroughly explained the marking criteria in terms of quantity and content of individual posts (over discussion time), as well as, tone and mechanics, collaboration between group members, quality of arguments in the final response and bonus points for wrapper and presenter roles (Figure 3-4).

3.3.3 Group Discussion Space Configurations

Each group had access to their private discussion space inside LMS used in the course. Only students within the group and teaching staff had access to this private space. This discussion space was composed of one page. This page included a discussion topic section at the top of the page and the discussion thread section at the bottom. The discussion topic section included (Figure 3-4):

1. Discussion task description
2. Link to Learning Analytics Visualization
3. Link to the study participation instructions

Discussion task instructions included the discussions topic questions, participation guidelines and marking criteria as described in details in Section 3.3.2.

Discussion Topic

Question: **"In a course like IAT 352, it is/it is not important that students learn how to program web applications in the programming/scripting language X."**

Discuss and come up with pros and cons arguments for the statement. Support with facts/sources. Discuss what X should be, and why.

How am I doing in this discussion?

Sign here to participate in the research study. You will have a chance to win a $50 gift card.

Discussion Participation Guidance

You are expected to engage in the discussion that will explore different aspects of the question itself, propose different ideas to address these aspects, select some ideas and justify why these were included and other rejected, and finally decide on the answer with a clear rationale.

Everyone is expected to participate meaningfully to the discussion. Your contributions have to be at the appropriate level and depth. The following contributions are expected at each level:

-Identify aspects to explore (1-3 messages from each participant) – engage in an analysis of the question being asked, as a group come with set of aspects that should be explored to address the question.

-Explore ideas to address the aspects (2-4 messages each) – do individual research to explore the aspects, integrate material from the readings for the class, and post your finding to share with others. Read others' posts, build on their ideas or argue the points they brought up by bringing new evidence or interpreting existing evidence and points in the discussion so far.

-Integrate ideas (1-3 posts each, moderated by synthesizer role) – participate in constructing a meaningful response from ideas raised in the previous posts. Select well-supported ideas to use in shaping group's position on the question, decide on the way to structure the response. Final response – 1 message for the group posted by wrapper role.

Debate - We will have a debate in the class. A presenter will be representing the group. As a presenter you may be assigned to argue for the position that is not consistent with your groups conclusion, hence your ability to use all the arguments discussed is essential for successfully arguing the case.

Marking

You are expected to post a minimum of 4 posts as follows: **minimum 1 post within first 2 days, minimum 2 posts on days 3-5.** For expected quality of messages see the marking rubric below.

This discussion activity worth 5% of the course mark. The 5% comprises of the following components:

Marking Rubric

20% Quantity – reading and posting as specified for each message category
30% Content – based on posts within each category

- Below average: Message tends to address peripheral issues and/or ramble. Tendency to recite facts and provide opinions. Important concepts not discussed.
- Average: messages tend to provide good general contributions, but may not always directly address discussion topics. Assertions are not always supported by evidence. Avoids unsupported opinions. Relevant concepts included into the discussion and connected well.
- Above average: messages are characterized by conciseness, clarity of argument, depth of insight into theoretical issues and working with relevant concepts, originality of treatment, relevancy, and sometimes include unusual insights.

20% Collaboration – engaging in the dialogue with others' ideas presented in the posts.
10% Tone & Mechanics – conducting yourself appropriately in a professional relationship. The messages are carefully formulated with minimum of spelling and grammatical errors.
20% Quality of arguments in the final response (and presentation) – shared by all group members.
The wrapper and presenter will receive up to 1% extra mark for their work

Debate - We will have a debate in the class. A presenter will be representing the group. As a presenter you may be assigned to argue for the position that is not consistent with your groups conclusion, hence your ability to use all the arguments discussed is essential for successfully arguing the case.

Figure 3-4: Discussion Topic Section in Discussion Group Space. Main Components: 1: Discussion Task Description, 2- Link to Learning Analytics Visualizations, 3- Link to Experiment Participation Instruction

The Learning Analytics Visualization was accessible through the thumbnail provided in group discussion page. The thumbnail was a small static snapshot of the three visualizations cascaded with the caption “How am I doing in this discussion?” (Figure 3-4). Once clicked on, the visualization would open up in a new tab and redirect to the visualization the student was assigned to. Because of the constraint on integration of external tool in the LMS, we could not have the visualizations displayed directly in the group discussion page. Therefore, we had to provide it as link on the discussion page.

Instructions on how to participate in the study were provided on a page inside the course container. This page was also linked to group discussion page.

3.4 Courses, Discussions and Participants

The study was replicated across 3 different blended courses (Table 3-1). These courses were 2nd (C2 and C1) and 3rd year level (C3) undergraduate offerings from Spring 2015 in a multidisciplinary Media, Arts and Technology program in a Canadian post-secondary institution. They varied in size with respect to number of enrolled students from small (C3), to medium (C2) and to large (C1).

Table 3-1: Course Specifications

Course ID	Course Name	Description	#students
C1	Introduction to Game Studies	An introduction to the medium of games through various lenses (games design, experience and culture) and a review over history of games from board and card games through the latest digital games	203
C2	New Media Images	An introduction to historical, aesthetic, theoretical and practical issues in digital video production.	96
C3	Internet Computing Technologies	An introduction to principles of Internet computing and technologies for building Web applications	29

Total of 5 discussion tasks were introduced in the study. C1 and C2 included only 1 discussion while C3 had 3 different discussion tasks in its course design. The discussion task design was based on the guidelines described earlier with small variations to fit the

course such as the discussion question, discussion time period, details of marking rubric breakdown and dynamics of the groups in terms of the size and method of selection. Table 3-2 shows the specifications of all discussions and discussion group formats.

Table 3-2: Discussion task specifications in each course

Course ID	Discussion ID	Discussion Topic	Group Assigned by	#Discussion Groups	Discussion Group Size	Discussion Duration(days)
C1	D1	Magic Circle	Instructor	20	10-11	14
C2	D1	Narrative Form	Students	26	3-4	7
C3	D1	Web Programming Language	Instructor	6	4-6	9
	D2	Big Data	Instructor	5	5-7	14
	D3	Cloud Computing	Instructor	6	4-5	9

Table 3-3 presents assignments of all students to each experimental condition per discussion across courses. Discussions included all of the three experimental conditions except for discussion D1 in C3. In that discussion students had access to one of the two Learning Analytics Visualizations (Top Contributors and Quality) because the Class Average visualization was in the implementation phase at that time.

Table 3-3: Number of students assigned to each experimental condition in each discussion for all courses

Condition	C1	C2		C3		
(Visualization)	D1	D1	D1	D2	D3	All
Class Average	70	34	N/A	11	11	126
Top Contributors	76	31	11	10	10	138
Quality	57	31	19	9	9	125

Number of students who took an additional step to participate in the study and completed the questionnaires is reported in Table 3-4.

Table 3-4: Number of participants in experimental condition for each discussion for all courses

Condition	C1	C2		C3		
(Visualization)	D1	D1	D1	D2	D3	Total
Class Average	25	8	N/A	7	7	47
Top Contributors	23	7	5	4	4	43
Quality	13	5	11	5	5	39

Demographics and background information for the 102 student who participated in the study are provided in Table 3-5.

Table 3-5: Participants' demographics and background information

Variables	n	%
Gender		
Female	35	34%
Male	67	66%
Age		
18 to 24	93	91%
25 to 34	7	7%
45 to 54	2	2%
Current year in the Program		
1st year: 1%	1	1%
2nd year: 33%	34	33%
3rd year: 31%	31	31%
4th year: 24%	24	24%
5th year and above: 11%	12	11%
Familiarity with Technology		
Not at all: 1%	1	1%
Slightly: 4%	4	4%
Somewhat: 19%	19	19%
Moderately: 39%	40	39%
Extremely: 37%	38	37%
Familiarity with Online Learning Environments		
Not at all	4	4%
Slightly	20	20%
Somewhat	23	23%
Moderately	45	43%
Extremely	10	10%
Familiarity with LMS		
Slightly	12	12%
Somewhat	13	12%
Moderately	61	60%
Extremely	16	16%
Familiarity with Online Discussions		
Not at all	7	7%
Slightly	14	14%
Somewhat	26	25%
Moderately	38	37%
Extremely	17	17%

3.5 Experiment Procedures

Within this study, instructors from several courses were approached to allow for recruiting students in their courses and prepare discussion task as described in Section 3.3.2. The courses were selected such that the discussion activity could be

pedagogically useful in their context. Decision was made based on the principal investigator's familiarity with the objectives and instructional design of the courses. A set of guidelines and samples were provided for the instructors to help them design the discussion activity accordingly and make sure that there is certain level of consistency across courses. These guidelines were prepared based on existing research on pedagogical values of discussions and instruction on how to design and facilitate effective discussions as explained in Section 3.3.1. Due to instructional design and imposed constraints of the course some suggested aspects including group size, weight of discussion activity in final course grade and items covered in the participation marking rubric were slightly modified by the instructors and other teaching staff. Also in courses with one discussion activity, it wasn't possible to rotate the roles. Instructors were also provided with details about the study and mockups of the Learning Analytic Visualizations.

Those instructors that agreed to participate went through the process of the discussion design review with the research team. All the details (i.e., discussion questions, group selection, participation requirements and marking criteria) were finalized after couple of face-to-face meetings and online correspondence. In the next step, the instructors were asked to prepare a list of concepts related to the topic of discussion as a required input for one of the visualizations (Quality). These were a set of concepts that the instructor expected the students to talk about while engaging in discussion with the peers.

Then one of the research team members was assigned a Designer role in the course space inside LMS for technical configurations. Using that role, the group discussion spaces were configured and Learning Analytics Visualizations were employed. The role was maintained throughout the discussion period for troubleshooting the technical issues.

The discussion task and the study were introduced to students in a lecture session before the discussion time period started. The instructor explained the educational aspects of the discussion task to students and its relevance and importance in the context of the course. Students were briefed that their participation in the discussion task was mandatory and would be counted towards their final grade.

In addition, one of the research investigators was present to introduce the study and invite students to participate. Students were informed that their participation was voluntarily and that as a reward, enrolled participants would be included in a lucky draw to win a $50 gift card (One out of every 20 participants would win a gift card). Those who

were willing to participate were asked to follow the instructions described in the class (also available as a link on the group discussion page in LMS Section 3.3.3). The participants were asked to sign the consent form, fill in the questionnaires as mentioned in Section 3.6.2 and continue to engage in discussion task as if they did not participate in the study.

Moreover, through a step-by-step demonstration in LMS, the research investigator guided students on how to access the discussion task and visualizations. All the students were notified that using Learning Analytics Visualization was voluntarily but they were advised to use it to inform themselves about how they are doing in the discussion.

3.6 Data Collection and Measurement

In this study, data was collected through 2 main sources in each of the 3 courses under study: log data of all students' as secondary data (Section 3.6.1) and questionnaire responses (Section 3.6.2) of the students who signed up to participate in the experiment.

3.6.1 Log Data

Several types of data were extracted from LMS logs:

- Discussion group structures and members
- Content of posted messages
- Time stamped log data of students' interaction within the LMS

To clean data and prepare for measurement, the initial step was to extract interactions that happened within the discussion time period (first day of discussion until the last activity in that discussion). For every discussion in each course, all the recorded interactions outside this timeframe were filtered out. Followed by that, interactions were coded. These codings classified activities related to discussion and those that were unrelated (Table 3-6). We consider only those discussion activities that were associated with the group discussion task in our study.

Table 3-6: LMS Interaction Codings

Interaction Coding	Description
Discussion Activities	
View Discussion	Activity that involves going to group discussion space which includes the whole discussion thread, discussion task description, link to Learning Analytics Visualization and link to study participation page
Post	Activity that involves posting a message
View Visualization	Activity than involves viewing Learning Analytics Visualization
Other Activities	Any Interactions unrelated to the group discussion

Having the coded interactions for every student in each discussion in each class, computing the count of activities was straightforward (e.g., count of posting activities, count of visualization view activities). The next complex challenge was to identify learning sessions in LMS and compute the time on task for each of the activities. Since the LMS stores a timestamp for every recorded interaction in its database, we calculated time on task by subtracting timestamp of the current activity from the timestamp of the subsequent activity. Although trace data contained an indicator for when a learning session ended, it was only limited to cases where the student manually logged off or the system automatically logged off after a certain time. Therefore, some values of time on task were above expectations (couple of hours, or even days). To handle this issue, sessions were identified. Whenever, there was a direct indication of end of session in the logs or the time on task of the activity was more than one hour, the activity was considered to be the last activity in the session. Then for all activities that were the last in a session, their time on task value was estimated by the median time spent on that activity type (e.g., view discussion) for a given student in that discussion. While different time on task estimation methods are reported in the literature, we chose median value which is as measure of central tendency less affected by outliers [41].

For the Post activity computation of time on task was different. Posting a message in LMS discussion space happens while discussion thread is being viewed (Discussion View Activity) and LMS database only records the timestamp for when the message was posted and not the time when the student started writing the message. Not having the accurate data, time on task for Post activity was adjusted to zero. After the Post activity, student is automatically redirected to discussion page. Therefore, the time gap between Post activity and the next interaction was counted towards Discussion View activity.

For some of the analysis, we needed to know when in the session an activity occurred. Due to deployment limitations of our study (Briefly explained in 3.3.3), Learning

Analytics Visualization could only be accessed through the discussion page inside LMS. Therefore, whenever a student wanted to engage in Visualization View activity, he first had to go to the discussion page to access the visualization. Hence, for analysis purposes, we removed any View Discussion activity that was directly followed by View Visualization activity in less than 5 seconds. The 5 seconds was the estimated time that was required for the student to go directly to the discussion page and click on the link to visualization page without engaging in any other activity.

3.6.2 Instruments (Questionnaires)

For those students who further participated in the experiment, the questionnaire results were also collected about their personal factors. Demographics data about students' age, gender, and current year in the program was collected through a questionnaire. In addition, background information was captured to understand students' overall familiarity with technology, prior experience with online learning environments particularly the Learning Management System and online discussions.

The 3×2 AGQ instrument was used to investigate students' Achievement Goal Orientations [16]. It consists of 18 items, grouped into 6 scales corresponding to achievement goals (task-approach, task-avoidance, self-approach, self-avoidance, other-approach, and other-avoidance, whereby self and task represent mastery goals and other represents performance goals. The responses were recorded on a Likert-type scale, from 1 (not at all true of me) to 7(very true of me). The total scores on every 3 items corresponding to a scale were used as the overall measure on that AGO scale. In case of 1 missing value in each scale, that value was replaced with average score of the other 2 items and total value was computed. If more than 1 value was missing, the total measure was assumed to be unknown.

3.7 Data Analysis

3.7.1 Coh-Metrix Analyses

Discourse analysis can be used to help identify effectiveness of discussions and quality of argumentations in collaborative learning environments [60]. We used Coh-

Metrix, a computational linguistics facility, to analyze content of the messages posted by students based on some higher-level features of discourse [29, 47]. Coh-Metrix[8] is structured according to multilevel theoretical frameworks for discourse comprehension, cognition and learning. Such discourse features can be revealing of some learning dependent constructs that cannot be directly measured. Coh-Metrix provides over 100 measures at 5 levels: 1- words, 2- syntax, 3- the explicit textbase, 4- the situation model, and 5- the discourse genre and rhetorical structure. A recent study identified 5 latent components that explained over 50% of the variance on a corpus of around 37,520 texts [29]. We used these 5 measures as described below:

- *Narrativity:* reflects the degree to which the text is in narrative and conveys a story, with characters, objects, events, actions and emotions typical in everyday oral communication. On the opposite end of the spectrum are expository/informational text.

- *Deep Cohesion:* reflects the degree to which the ideas in the text are cohesively connected at a mental and conceptual level that shows causal, intentional, temporal and spatial connections.

- *Referential Cohesion:* reflects the degree to which explicit words and ideas in the text are overlap with each other across sentences and the overall text

- *Syntactic Simplicity:* reflect the degree to which sentences have lower number of words and use more simple and familiar structures rather than dense sentences and high frequency of embedded phrase

- *Concreteness:* reflects the degree to which the text includes words that are concrete, meaningful, and induce mental images in contrast to abstract words.

In this study, the five principal component of Coh-Metrix were computed for each message. Then for each student in each discussion the average measures of all messages were computed for analysis. Only the messages that included at least one of the key concepts related to discussion topic (as identified by the instructor) were included in this analysis. These are the messages gauged to have traces of Cognitive Presence.

[8] www.cohmetrix.com

3.7.2 Hierarchical Linear Mixed Models

To address our research questions described in 3.1, we adopted hierarchical linear mixed models analysis [52]. Due to the nested structure of the data and the crossed variables in our analysis we identified hierarchical linear mixed models to be a suitable method. This is a common method of analysis for studies of this type [14, 35, 36]. The mixed models consist of a combination of fixed and random effects and can be exploited to evaluate the influence that the fixed effects have on dependent variables after accounting for the random effects.

Using a hierarchical mixed-model approach we examined the contribution of engagement with Learning Analytics Visualizations on students' posting behavior (quantity and quality) by controlling for the variance associated with the nested structure of individual students within different courses. This is to find out if those who used the Learning Analytics Visualizations versus those who did not were associated with different posting behaviors and for those who used the Learning Analytics Visualizations their level of usage influenced their posting behavior. Further, we investigated the effect of different visualizations on students' level of engagement with the Learning Analytics Visualizations and the influence on their posting behavior (quantity and quality). Finally, we included students' personal factor to see the effect of Learning Analytics Visualization on the above dependent variables after controlling for their self-reported Achievement Goal Orientations.

3.7.2.1 Model Fit Assessment

One linear mixed model was selected for each question. The choice of the best fitting model for the dependent variable in the question was finalized after several steps of model construction and fitness comparison:

1- Construct a *null model* with *student within a course* as the only random effect[9].

[9] Within our analysis we initially considered discussion groups and discussion topics as additional levels in the nested structure of the random effect. In some cases the model did not meet the convergence criteria. In other cases, adding either or both of these two variables did not result in a better model than the model containing students within a course. Hence, they were removed from the nested random effect. In addition, another possible covariate we considered was the total activity count of students inside LMS throughout the discussion period to control for the variation

2- Construct several *fixed effects* models that included the nested random effect in the null model, as well as, a combination of predictor variables in the research question as fixed effects: 1)individual predictor variables 2) all predictor variables and 3- all predictor variables and their interactions (if their interaction was relevant to the research question). Then, compare these models and select the one that is a better fit than the others

3- Compare the best fit model in step 2 with the null model in step 1 to find out if predictor variables can predict the dependent variable beyond the random effects.

Several criteria were used to make comparison between models. Akaike Information Criterion (AIC) and likelihood ratio test [23] were used to decide the best fitting model. Primarily we looked at AIC for the two models under the comparison. The model with lower (AIC) was suggested to have a better fit. We used the likelihood ratio test to confirm AIC result. If the likelihood ratio test did not yield a significant difference, typically the simpler model (with the less number of variables) was chosen. We also calculated an estimate of effect size (R^2) for each model which reveals the variance explained by the model [75].

3.7.2.2 Analysis of the Fixed Effects in the Final Model

After model construction and comparison, if the fixed effect model yielded a better fit than our null model, we further analyzed the output of the fixed effect model in terms of the fixed effects. In models with a categorical variable as the fixed effect (categorical predictor), the first level of that categorical variable is used as reference level (intercept) and the estimated coefficients (β) for remaining levels are tested against that reference. These differences can be interpreted as the difference between the dependent variables if they are on normal scales (e.g., the mean value of count of posts is a unit higher for users compared to non-users) or scaled differences in the dependent variable.

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caused by overall activeness of students that may have been wrongly attributed to the effect of a particular Learning Analytics Visualization. Our findings showed that considering this random effect did not yield a better model. In addition, it did not influence the contribution of fixed effects to the predictor variable in our research questions.

If we have a continuous variable as fixed effect (continuous predictor) in addition to categorical variables but without the interaction between them, the estimated coefficient (β) for the continuous variable shows the change in dependent variable associated with an increase of 1 unit in the predictor (average slope). If the model also includes interaction term between a categorical and the continuous variable, the estimated coefficient for the continuous variable is based on the reference level for categorical variables not all levels (average slope for those observation that the categorical variables is in its reference level). Therefore, we do not report main effects of continuous variables when we have the interaction term. In the interaction model, the estimated coefficient for Interaction terms can be interpreted as the difference in the slopes of the continuous variables between a certain level of categorical variable and the reference level of it.

Summary of the analysis of fixed effects presented in tables in later section includes the coefficients (β) as explained above and also indicates significant differences with respect to the reference level selected. Further we investigate if the main effect of categorical predictor and continuous predictor and the interaction between the two is significant. Looking at the estimated coefficients for continuous variables we determine direction of effect (positive/negative) effect. For categorical variables we can look at the contrast between reference levels with all other levels just by looking at the summary of the model which is reported in tables (Analysis of the fixed effects for the model) which reports p-values. However, if there are more than two levels and pairwise comparison between all levels is of interest, we can compare estimated least square means using t-test.

Probing the contrast between different levels of interaction term (continuous and categorical) is also apparent from the summary of model. However, looking at the coefficient for the interaction terms only show the relative slopes of the continuous variables for certain level of categorical variable with respect to reference level of it. Again if we need pairwise comparison we can perform z-test on the model to compare these coefficients across all levels and report all p-values. In this case to find out the direction of effect of continuous variables on dependent variables at a certain level of categorical variables, we have to compute absolute slope (relative slope of at certain level + slope of at reference level).

4 Results

Since the students' use of Learning Analytics Visualizations was voluntary, not all the students chose to engage with the visualization. The count of Visualization View activities for each student in a discussion that belongs to a particular course was measured as described in 3.6.1. Based on these counts we identify an additional classification of students. Users are a subset of students who engaged with the visualization more than once. They returned to Learning Analytics Visualization after the first time (at least once more), knowing what the visualization offers. They are considered the actual User of Visualizations. Also we mentioned in Section 3.4 that a smaller group of students further participated in the research study by submitting the questionnaires. Therefore, similar classification applies to the participants who engaged with the visualization more than once. They are called Participant Users. Table 4-1 and Table 4-2 provide more details on these classifications which are later used in our analysis.

Table 4-1: Classification of students

Group Name	Definition
Assigned to	Set of all students assigned to each Learning Analytics Visualization
Users	Subset of students "Assigned to" each Learning Analytics Visualization who engaged with the visualization more than once through the discussion period.
Participants	Set of students assigned to each Learning Analytics Visualization who submitted the questionnaires.
Participant Users	Subset of "Participants" who engaged with Learning Analytics Visualization more than once through the discussion period.

Table 4-2: Number of "Users" and "Participant Users'' for each Learning Analytics Visualization

Visualization	C1		C2		C3							
	D1		D1		D1		D2		D3		All	
	#Users	#Participant Users	#Users	#Participant Users	#Users	#Participant Users	#Users	#Participant Users	#Users	#Participant Users	#Users	#Participant Users
Class Average	36	17	13	6	N/A	N/A	5	5	4	4	58	32
Top Contributors	40	12	11	4	2	2	2	1	1	0	56	19
Quality	25	8	13	3	5	4	4	3	4	3	51	21

To explore Users engagement with Learning Analytics Visualizations over time, we plotted number of Users who viewed Learning Analytics Visualizations over their discussion sessions. Users differ with respect to the number of discussion sessions they participate in (i.e., number of discussion sessions they are active) (Table 4-3). Therefore, the plot was overlaid with the number of active users in each session (users who participate in at least one discussion related activity in that session) (Figure 4-1).

Table 4-3: Count of active discussion session for "Users'' of each visualization

Visualization	Mdn(25%,75%)
Class Average	15.5(9,19)
Top Contributors	13.5(9,21.25)
Quality	11(8,19)

As expected, the number of active users decreases as the discussion session increases. It can be observed that the number of active users drops sharply for the users of the Class Average visualization, while the declining slope for the other two visualizations is less sharp. Also, the number of users who engaged with the Learning Analytics Visualizations reduces strongly and becomes rare after 19 sessions for the Class Average visualization. For the Users of the Quality visualization engaging with visualization continues up to 30 sessions. Finally, for the Top Contributors visualization it continues to their 35th discussion session.

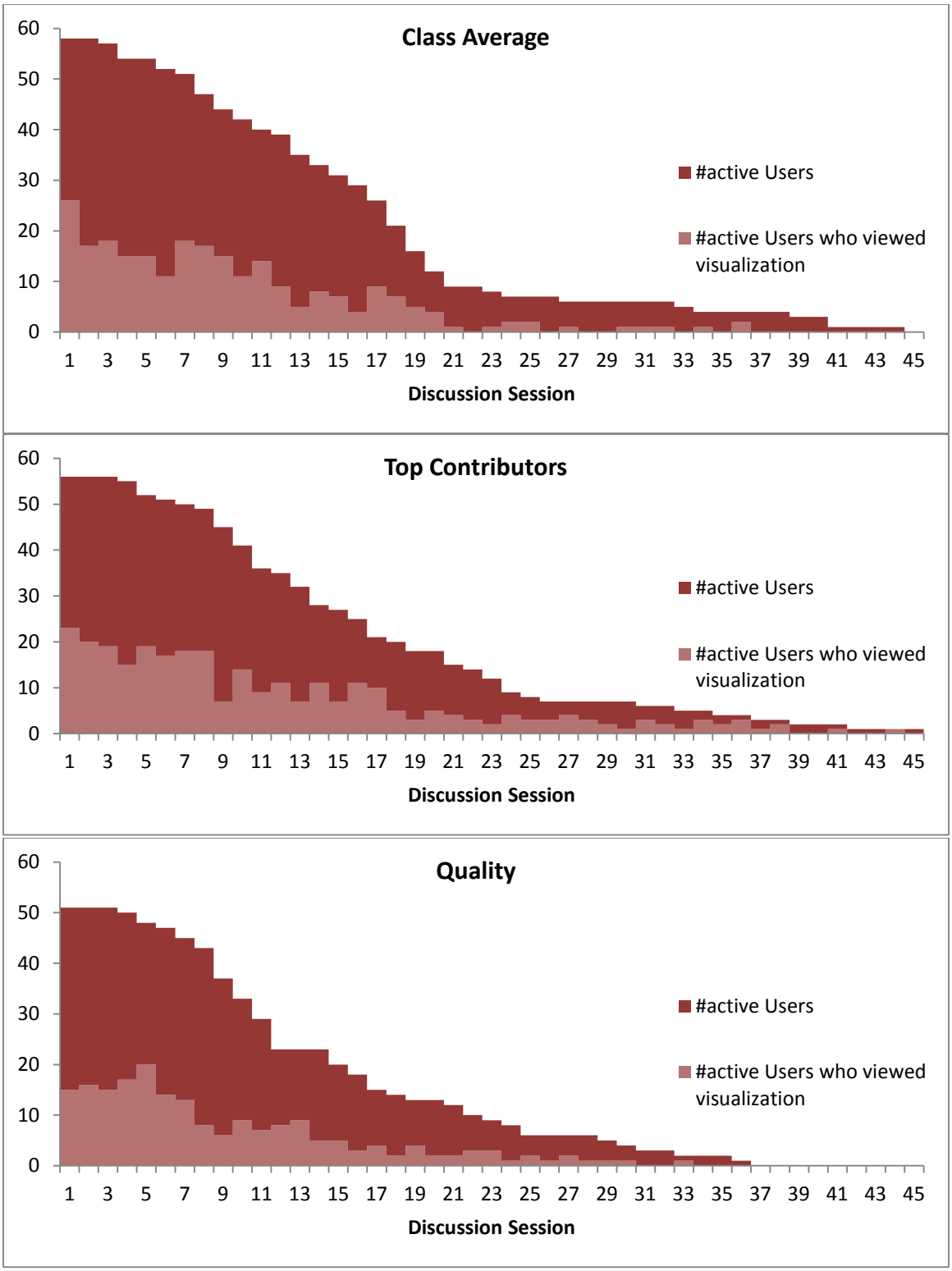

Figure 4-1: Distribution of Visualization View activities across discussion sessions

4.1 RQ1: Is there an effect of the visualization type on the users' level of engagement with Learning Analytics Visualization?

Table 4-4: Variables in RQ1

Variable	Description	Type
Predictor Variables		
Learning Analytics Visualizations	Experimental condition (The Learning Analytics Visualization user can access)	Categorical
Dependent Variables		
Count of Visualization Views	Total count of Visualization View activities by the user	Continuous

Table 4-5 demonstrates Visualization View activity counts (median, 25th and 75th percentile) for Users of each of the 3 visualizations. These values are measured per discussion belonging to one of the three courses as explained in 3.6.1.

Table 4-5: Count of Visualization View activities for "Users'' of each visualization

	C1	C2	C3			
	D1	D1	D1	D2	D3	All
Visualization	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)
Class Average	5(3,8.25)	4(2,6)	N/A	5(5,16)	6(3.5,10)	5(3,8)
Top Contributors	5.5(3,13)	3(3,6)	9.5(6.25,12.75)	8.5(5.75,11.25)	11(11,11)	5(3,11)
Quality	5(3,15)	5(3,10)	3 (3,10)	4.5(3.75,5.5)	7.5(4.5,10)	5(3,10)

Following the model fit assessment procedure, it was observed that adding a fixed effect of Learning Analytics Visualization did not yield a model with a fit better than the null model. On that account, no significant effect of the visualization type on users' level of engagement with Learning Analytics Visualizations was found. The model comparison is reported in Table 4-6.

Table 4-6: Inferential Statistic for Model fit assessment RQ1

	X^2	df	R^2	AIC
Null Model			0.35	1112.42
Fixed Model	3.01	2	0.33	1113.40

$\chi 2$ values show the differences between the model in the current row and the model in the previous row.
Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05

4.2 RQ1.1: Is there an effect of visualization type on the users' level of engagement with Learning Analytics Visualizations when controlled for their self-reported Achievement Goal Orientations?

Table 4-7: Variables in RQ1.1

Variable	Description	Type
Predictor Variables		
Learning Analytics Visualizations	Experimental condition (The Learning Analytics Visualization participant user can access)	Categorical
Co-Variate Variables		
AGO Scale Scores	Participant user's self-reported scores on 6 AGO scale (Task-Approach, Task-Avoidance, Self-Approach, Self-Avoidance, Other-Approach and Other-Avoidance)	Continuous
Dependent Variables		
Count of Visualization Views	Total count of Visualization View activities by the participant user	Continuous

Table 4-8 presents Visualization View activity counts (median, 25th and 75th percentile) for Participant Users of each of the 3 visualizations. These values are measured per discussion belonging to one of the three courses as explained in 3.6.1.

Table 4-8: Count of Visualization View activities for "Participant Users" of each visualization

	C1	C2	C3			
	D1	D1	D1	D2	D3	All
Visualization	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)
Class Average	7(4,9)	(4.25,7.25)	N/A	5(5,16)	6(3.5,10)	6.5(4,9)
Top Contributors	6.5(4,20.25)	3(2.75,5)	9.5(6.25,12.75)	14(14,14)	N/A	6(3,15)
Quality	6.5(3.75,13.5)	6(5.5,9)	3(3,4.75)	4(3.5,4.5)	5(4,7.5)	5(3,10)

The goodness-of-fit comparison between the null model and the fixed effects model indicated that the model with AGO scale scores as fixed effects was significantly a better fit than the null model (Table 4-9). However, further analysis on this model did not reveal significant main effects of any of the six AGO scales (Further details in Table 4-10).

Table 4-9: Inferential Statistic for Model fit assessment RQ1.1

	χ^2	df	R^2	AIC
Null Model			0.35	220.25
Fixed Model(AGO Scales)	13.42*	6	0.46	218.83

χ2 values show the differences between the model in the current row and the model in the previous row.
Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05

Table 4-10: Analysis of the fixed effects for the model RQ1.1

Variable	B	SE	95% CI	
			Lower	Upper
Intercept	0.527	0.153	0.220	0.834
TaskAp	-0.190	0.192	-0.573	0.193
TaskAv	0.132	0.241	-0.350	0.614
SelfAp	0.183	0.248	-0.313	0.680
SelfAv	-0.124	0.347	-0.819	0.571
OtherAp	-0.333	0.267	-0.867	0.202
OtherAv	0.534	0.322	-0.109	1.177

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, . p<0.1 (marginal)
All variables are scaled

4.3 RQ2: Is there an effect of using Learning Analytics Visualizations on the students' count of posts?

Table 4-11: Variables in RQ2-Quantity

Variable	Description	Type
Predictor Variables		
Visualization Engagement	Whether student engaged the visualization or not (users/non-users)	Categorical
Dependent Variables		
Count of Posts	Total Post Count activities by the student	Continuous

Table 4-12 demonstrates Post activity counts (median, 25th and 75th percentile) for Users of each of the three visualizations. These values are measured per discussion belonging to one of the three courses as explained in 3.6.1. To compare posting quantities

of Users and Non-Users[10], the post counts of Non-Users were also measured and presented in Table 4-13.

Table 4-12: Count of Posts for "Users" of the Learning Analytics Visualizations

	C1	C2		C3		
	D1	D1	D1	D2	D3	All
Visualization	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)
Class Average	5 (3,6.25)	7(6,8)	N/A	3(3,4)	3.5(2.5,4)	5(3,7)
Top Contributors	5 (4,6)	6(5.5,7.5)	3(3,3)	3(2,4)	2(1,4)	5(3.75,6)
Quality	4(4,5)	6(5,6)	3(3,5)	3(2.5,3.25)	3.5(2.75,4.5)	4(3,6)

Table 4-13: Count of Posts for "Non-Users" of the Learning Analytics Visualization

	C1	C2		C3		
	D1	D1	D1	D2	D3	All
Visualization	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)
Class Average	3(1.25,4)	6(4,8)	N/A	1(1,1.75)	2(1,3.5)	3(2,6)
Top Contributors	3(2,5)	6.5(3.75,8)	2(2,3)	2(1,3)	2(1,4)	3(2,5)
Quality	3.5(1.75,5)	6.5(5,7)	2(1.25,3.75)	3(1,4)	3(2,4)	4(2,5)

AIC and the likelihood ratio test indicated that the fixed model with Visualization Engagement as the fixed effect yielded a significantly better fit than the null model (Table 4-14). The linear mixed-effect analysis showed a significant main effect for Visualization Engagement, $F(1,350.27)=13.76$, $p<0.001$ (Further details Table 4-15). According to this, the students who were the users of the visualization had significantly higher count of posts in comparison with the non-users ($t(350.3)=-3.71$, $p<0.001$, 95% CI [-1.33, -0.41]).

[10]Users are subset of students "Assigned" to each Learning Analytics Visualization who engaged with the visualization more than once through the discussion period. Non-users are those who were assigned to Learning Analytics Visualization but did not check the visualization at all or only checked it once (Section 4).

Table 4-14 Inferential statistic for model fit assessment RQ2-Post Count

	χ2	df	R^2	AIC
Null Model			0.82	1761.56
Fixed Model(Visualization Engagement)	13.41***	1	0.82	1750.16

χ2 values show the differences between the model in the current row and the model in the previous row.
Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05

Table 4-15: Analysis of the fixed effects for the model RQ2- Post Count

Variable	β	SE	95% CI	
			Lower	Upper
Intercept*	3.979	0.835	2.309	5.469
Visualization Engagement (Users)***	0.868	0.234	0.400	1.336

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, · p<0.1 (marginal)
All variables are on a normal scale

4.4 RQ2.1: For the users, is there an effect of level of using Learning Analytics Visualizations on their count of posts?

Table 4-16: Variables in RQ2.1-Quantity

Variable	Description	Type
Predictor Variables		
Visualization Engagement Percentile	How much user engaged with the visualization (4 groups of users based on the count of Visualization View percentiles)	Categorical
Dependent Variables		
Count of Posts	Total count of Post activities by the user	Continuous

To find out if there is a relationship between the level of engagement with the Learning Analytics Visualizations and the quantity of posting behaviors, we classified Users of each Learning Analytics Visualization to four groups based on their count of Visualization View activities (Low Users group include Users whose count of Visualization Views is below or equal to 25th percentile for a particular Learning Analytics Visualization (values computed in Table 4-5). The Low-Mid Users group consists of Users whose count of Visualization Views is higher than 25thpercentile and lower or equal to 50th percentile. The Mid-High Users group involves Users with the count of Visualization Views higher than 50th percentile and lower than or equal to 75th percentile. Finally, the High Users group contains Users with the counts of Visualization Views higher than 75thpercentile). For each group, we computed the median value for the Post activity counts as presented in Table 4-17. Accordingly, the median count of posts for High Users is more than other

groups of Users for all Visualization types. The overall number of High Users was 37, Mid-High Users 36, Low-Mid Users 37, and Low Users 55.

Table 4-17: Count of Posts for "Users" of each visualization based on level of usage

	Usage Level of Learning Analytics Visualization*			
Visualization	Low Users Mdn(25%,75%)	Low-Mid Users Mdn(25%,75%)	Mid-High Users Mdn(25%,75%)	High Users Mdn(25%,75%)
Class Average	4.5(2.25,7)	4(3,6.5)	5(4,6.5)	5.5(4.25,7)
Top Contributors	5(3.5,6)	5(3,6)	5(4,5.5)	6(4.5,8)
Quality	4(3,6)	4(2,5)	5(4,5)	5(4,6.25)

*Usage level groupings is based on quartiles of visualization view counts for users of each Visualization Low Users: (0%-25%), Low-Mid Users: (25%,50%), Mid-High Users: (50%-75%) and High Users: (75%-100%)

AIC and likelihood ratio test indicated that the fixed model with Visualization Engagement Percentile as the fixed effect yielded a significantly better fit than the null model (Table 4-18).The linear mixed-effect analysis showed a significant main effect for Visualization Engagement Percentiles, $F(3,111.41)=5.22$, $p<0.001$ (Further details in Table 4-19).

This effect was probed further by exploring pairwise comparisons. Accordingly, High Users had significantly more posts than both Low Users ($t(112.7)=-3.38$, $p<0.001$, 95% CI [-1.33, -0.41]) and Low-Mid users ($t(106.4)=-3.56$, $p<0.001$, 95% CI [-2.77, -0.79]). In addition, counts of posted messages by High users was marginally higher than that of Mid-High Users ($t(105.1)=-1.80$, $p<0.1$, 95% CI [-1.89, 0.09]) which was also marginally higher than that of Low-Mid users ($t(126.4)=-1.72$, $p<0.1$, 95% CI [-1.90, 0.13]).

Table 4-18: Inferential Statistic for Model fit assessment RQ2.1-Post Count

	$\chi2$	df	R^2	AIC
Null Model		1	0.74	766.31
Fixed Model (Visualization Engagement Percentiles)	14.88**	3	0.78	757.42

$\chi2$ values show the differences between the model in the current row and the model in the previous row.
Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05

Table 4-19: Analysis of the fixed effects for the model RQ2.1-Post Count

Variable	β	SE	95% CI	
			Lower	Upper
Intercept (Low Users)**	4.377	0.791	2.796	5.959
Users (Low-Mid Users)	-0.226	0.500	-1.126	0.673
Users (Mid-High Users)	0.655	0.473	-0.290	1.600
Users (High Users)**	1.552	0.459	0.633	2.471

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, · p<0.1 (marginal)
All variables are on a normal scale

4.5 RQ2: Is there an effect of using Learning Analytics Visualizations on the students' quality of posts?

Table 4-20: Variables in RQ2-Quality

Variable	Description	Type
Predictor Variables		
Visualization Engagement	Whether student engaged the visualization or not (users/non-users)	Categorical
Dependent Variables		
Quality of Posts	Average values of the five principal components of Coh-Metrix (Narrativity, Deep Cohesion, Syntactic Simplicity, Referential Cohesion, and Concreteness) for all messages posted by the student that included at least one of the key concepts identified by the instructor	Continuous

Table 4-21 shows average quality of messages based on Coh-Metrix principal components (median, 25th and 75th percentile) for Users of each of the three visualizations. To compare average quality of messages posted by Users and Non-Users, Coh-Metrix components were also measured for Non-Users and presented in Table 4-22.

The model fit assessment procedure for all the five components of Coh-Metrix revealed that the null model was a better fit than the fixed effect model. According to this, the mixed model analysis did not find a significant effect of engagement with Learning Analytics Visualizations on the average quality of messages posted in the group discussion (Table 4-23).

Table 4-21: Average Quality Values of Posts for "Users" of the Learning Analytics Visualizations

	C1	C2	C3			
	D1	D1	D1	D2	D3	All
Visualization	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)
			Narrativity			
Class Average	51.99(0,66.79)	68.16(48.40,71.91)	N/A	23.88(23.24,31.74)	24.19(17.35,31.58)	49.71(23.56,68.12)
Top Contributors Quality	65.80(50.39,72.20)	50.17(42.55,60.21)	55.25(42.13,68.37)	19.75(11.67,27.83)	29.04(29.04,29.04)	59.17(43.29,71.96)
	64.99(55.43,70.36)	52.19(47.87,60.06)	47.48(40.51,52.49)	35.30(30.34,46.18)	42.03(33.20,49.69)	56.44(44.86,66.14)
			Deep Cohesion			
Class Average	67.54(0,91.11)	62.17(57.26,75.09)	N/A	42.49(31.75,54.55)	65.66(58.13,75.94)	61.86(42.87,83.63)
Top Contributors Quality	84.93(73.06,94.62)	60.48(49.69,67.99)	83.67(81.77,85.57)	37.91(30.28,45.53)	77.73(77.73,77.73)	78.49(61.18,92.10)
	70.30(58.28,89.30)	67.56(60.17,77.77)	68.62(59.89,74.88)	55.16(41.08,72.09)	60.67(52.36,70.54)	68.53(53.66,85.41)
			Syntactic Simplicity			
Class Average	22.78(0,45.42)	19.77(9.90,27.56)	N/A	28.16(27.24,45.54)	52.75(47.16,61.23)	25.79(9.79,45.32)
Top Contributors Quality	32.59(16.96,44.25)	16.70(11.64,30.94)	25.73(23.55,27.90)	64.85(56.55,73.24)	32.84(32.84,32.84)	30.94((16.19,43.56)
	25.86(17.46,34.78)	24.92(20.88,40.35)	38.53(31.25,46.23)	34.58(27.81,40.01)	31.86(21.59,43.13)	27.92(19.42,39.87)
			Referential Cohesion			
Class Average	47.30(0.68.14)	64.20(54.38,78.96)	N/A	42.89(30.87,60.82)	37.66(28.62,42.34)	54.15(30.09,69.30)
Top Contributors Quality	63.45(40.18,88.54)	63.50(57.74,79.04)	52.22(47.72,56.73)	12.20(10.77,13.63)	25.45(25.45,25.45)	60.12(39.02,85.75)
	73.45(61.77,89.42)	61.74(49.5144,62.67)	18.41(13.41,21.78)	42.47(40.63,47.44)	32.05(25.43,42.76)	61.84(43.18,74.01)
			Concreteness			
Class Average	32.00(0,61.58)	73.24(68.55,75.45)	N/A	21.10(19.82,47.99)	49.83(43.36,58.03)	47.99(26.50,70.75)
Top Contributors Quality	47.42(28.55,62.01)	71.98(65.53,82.91)	22.48(12.38,32.57)	35.18(34.43,35.94)	51.38(51.38,51.38)	50.33(32.71,66.80)
	47.12(38.20,62.08)	80.53(72.28,82.69)	18.94(13.56,23.44)	22.22(12.19,35.04)	33.45(26.70,39.14)	48.16(30.83,72.85)

Table 4-22: Average Quality of Posts for "Non-Users" of the Learning Analytics Visualizations

	C1	C2	C3			
	D1	D1	D1	D2	D3	All
Visualization	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)
			Narrativity			
Class Average	56.69(50.59,70.71)	61.09(51.50,69.25)	N/A	55.53(47.61,60.32)	45.39(38.15,54.92)	57.24(49.51,66.49)
Top Contributors	50.20(25.78,58.49)	59.36(46.28,68.79)	54.56(52.34,58.97)	34.83(23.65,43.99)	35.05(30.16,39.25)	50.22(37.49,60.51)
Quality	47.42(0,72.17)	61.72(50.10,73.61)	63.63(51.72,75.71)	45.95(20.05,61.79)	36.59(32.01,42.85)	54.00(36.05,69.99)
			Deep Cohesion			
Class Average	83.89(57.53,96.65)	57.67(41.61,72.94)	N/A	50.80(38.34,80.04)	88.72(81.55,97.13)	71.69(47.34,90.39)
Top Contributors	77.13(29.12,87.49)	68.00(56.68,77.35)	78.52(58.47,92.13)	51.90(32.14,77.31)	60.14(46.90,69.23)	68.33(46.34,82.89)
Quality	44.62(0,86.11)	71.95(41.22,83.66)	84.56(50.95,90.67)	62.55(56.01,68.44)	59.60(57.79,62.24)	62.71(34.82,85.09)
			Syntactic Simplicity			
Class Average	33.44(15.34,51.04)	23.67(16.28,26.66)	N/A	10.89(7.67,23.08)	42.18(17.81,54.89)	26.29(12.66,42.58)
Top Contributors	25.14(6.15,55.72)	20.91(12.50,27.78)	23.59(19.39,26.87)	41.06(20.84,55.89)	36.20(20.54,55.56)	24.39(12.93,44.67)
Quality	15.10(0,34.75)	21.98(13.76,32.33)	21.46(7.29,38.16)	27.43(24.74,29.81)	33.45(31.65,37.06)	22.50(5.15,36.11)
			Referential Cohesion			
Class Average	67.03(36.44,91.47)	69.80(54.07,81.99)	N/A	65.57(56.82,76.95)	28.34(11.69,38.83)	65.11(41.26,81.52)
Top Contributors	60.11(0.62,79.70)	63.83(50.52,79.03)	45.92(31.97,52.97)	44.43(26.18,61.55)	27.89(14.86,38.64)	52.13(32.30,74.44)
Quality	60.22(0,85.31)	68.96(59.29,74.43)	35.63(22.74,61.86)	66.98(21.50,79.95)	35.23(34.81,44.84)	58.55(22.74,74.43)
			Concreteness			
Class Average	47.78(29.77,72.91)	73.11(60.95,78.17)	N/A	27.73(15.51,37.49)	33.24(18.56,47.09)	59.55(31.32,74.31)
Top Contributors	38.21(12.74,69.93)	83.36(65.91,88.49)	17.18(12.73,21.06)	26.93(12.16,31.14)	41.02(20.02,58.58)	43.45(17.00,72.11)
Quality	42.46(0,60.12)	76.99(70.93,85.51)	7.20(4.68,13.87)	23.39(15.15,36.69)	32.59(14.12,45.30)	43.74(7.20,71.11)

Table 4-23: Inferential statistic for model fit assessment RQ2-Post Quality

Narrativity				
	χ2	df	R^2	AIC
Null Model			0.54	1005.90
Fixed Model	0.90	1	0.54	1007.88
Deep Cohesion				
	χ2	df	R^2	AIC
Null Model			0.10	1025.56
Fixed Model	0.36	1	0.12	1026.72
Syntactic Simplicity				
	χ2	df	R^2	AIC
Null Model			0.28	1019.25
Fixed Model	0.49	1	0.27	1020.76
Referential Cohesion				
	χ2	df	R^2	AIC
Null Model			0.42	998.70
Fixed Model	0.72	1	0.43	1000.57
Concreteness				
	χ2	df	R^2	AIC
Null Model			0.43	876.45
Fixed Model	0.54	1	0.43	878.08

χ2 values show the differences between the model in the current row and the model in the previous row.
Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05

4.6 RQ2.1: For the users, is there an effect of level of using Learning Analytics Visualizations on their quality of posts?

Table 4-24: Variables in RQ2.1-Quality

Variable	Description	Type
Predictor Variables		
Visualization Engagement Percentile	How much user engaged with the visualization (4 groups of users based on the count of Visualization View percentiles)	Categorical
Dependent Variables		
Count of Posts	Average values of the five principal components of Coh-Metrix (Narrativity, Deep Cohesion, Syntactic Simplicity, Referential Cohesion, and Concreteness) for all messages posted by the user that included at least one of the key concepts identified by the instructor	Continuous

For each group of Users, we computed the median value for the quality of posts based on Coh-Metrix principal components as presented in Table 4-25.

Table 4-25: Quality of Posts for "Users" of each visualization based on level of usage

	Usage Level of Learning Analytics Visualization*			
Visualization	Low Users Mdn(25%,75%)	Low-Mid Users Mdn(25%,75%)	Mid-High Users Mdn(25%,75%)	High Users Mdn(25%,75%)
		Narrativity		
Class Average	34.16(0.00,57.03)	49.71(23.88,60.53)	64.56(44.50,68.14)	50.10(42.70,66.89)
Top Contributors	54.68(41.08,68.04)	63.68(51.34,73.80)	57.06(48.95,67.07)	63.47(37.89,71.25)
Quality	51.45(41.33,62.82)	61.37(52.74,66.95)	39.63(31.54,53.59)	64.52(59.40,68.44)
		Deep Cohesion		
Class Average	44.25(0.00,68.60)	55.31(42.49,68.83)	76.43(56.64,93.58)	76.35(63.12,85.90)
Top Contributors	66.74(55.12,88.36)	79.37(60.95,92.07)	93.73(80.18,95.05)	76.61(72.90,83.27)
Quality	66.54(44.13,87.63)	69.44(52.63,70.34)	63.24(61.29,77.77)	72.36(62.29,76.97)
		Syntactic Simplicity		
Class Average	11.41(0.00,27.36)	25.79(16.87,31.14)	31.96(15.17,46.87)	45.17(33.10,63.58)
Top Contributors	30.07(16.39,42.36)	20.33(11.57,37.80)	30.99(21.30,62.17)	35.12(20.58,43.69)
Quality	20.88(17.71,35.11)	34.07(29.40,39.55)	39.71(35.92,57.03)	22.87(16.34,28.40)
		Referential Cohesion		
Class Average	52.24(0.00,80.17)	59.79(33.38,63.02)	56.90(34.65,65.64)	42.51(32.89,67.92)
Top Contributors	60.50(33.82,70.63)	52.57(39.91,84.30)	82.76(59.87,85.74)	59.46(34.38,87.73)
Quality	58.12(24.34,66.64)	49.33(44.77,61.70)	52.50(29.92,61.86)	74.57(66.25,88.73)
		Concreteness		
Class Average	59.39(0.00,72.65)	52.45(43.73,65.56)	36.90(29.25,67.26)	36.67(26.00,68.89)
Top Contributors	61.68(37.03,67.10)	46.81(25.39,50.33)	61.25(44.97,70.52)	58.32(25.12,67.77)
Quality	46.56(22.19,65.21)	60.09(32.46,79.75)	36.69(30.89,59.52)	57.08(45.38,72.80)

*Usage level groupings is based on quartiles of visualization view counts for users of each visualization Low Users: (0%-25%), Low-Mid Users: (25%,50%), Mid-High Users: (50%-75%) and High Users: (75%-100%)

4.6.1 Deep Cohesion and Syntactic Simplicity

For deep cohesion and syntactic simplicity, AIC and likelihood ratio test indicated that the fixed model with Visualization Engagement Percentile as the fixed effect yielded a significantly better fit than the null model (Table 4-26).

The linear mixed model for deep cohesion further revealed a significant main effect for Visualization Engagement Percentiles, $F(3,104.27)= 4.87$, $p<0.01$ (Further details in Table 4-27). This effect was probed further by exploring pairwise comparisons. Accordingly, High Users had significantly higher scores of deep cohesion of their posted messages than those posted by both Low Users ($t(109.1)=-2.93$, $p<0.01$, 95% CI [-2.93, -0.97]) and Low-Mid users ($t(100.7)=-2.10$, $p<0.05$, 95% CI [-0.88, -0.02]). In addition, scores of deep cohesion of their messages posted by Mid-High users was significantly

higher than those posted by both Low-Mid Users (t(116.5)=-2.38, p<0.05, 95% CI [-0.99, -0.09]) and Low Users (t(123.9)=-3.19, p<0.01, 95% CI [-1.08, -0.25]).

Further analysis of the syntactic simplicity model showed a significant main effect for Visualization Engagement Percentiles, F(3,151.19)=3.50, p<0.05 (Further details in Table 4-27). A pairwise comparison between the groups showed that High Users had significantly higher scores of syntactic simplicity than Low Users (t(152)=-2.13, p<0.05, 95%, CI [-0.84, -0.06]). Also Mid-High Users' scores of syntactic simplicity were significantly higher than those of Low Users (t(150.2)=-3.01, p<0.05, 95%, CI [-1.24, -0.21]).

Table 4-26: Inferential Statistic for Model fit assessment RQ2.1-Post Quality

Narrativity				
	$\chi2$	df	R^2	AIC
Null Model			0.59	444.18
Fixed Model	4.89	3	0.59	445.30
Deep Cohesion				
	$\chi2$	df	R^2	AIC
Null Model			0.27	444.82
Fixed Model	11.77**	3	0.70	439.05
Syntactic Simplicity				
	$\chi2$	df	R^2	AIC
Null Model			0.08	433.48
Fixed Model	0.02*	3	0.14	429.32
Referential Cohesion				
	$\chi2$	df	R^2	AIC
Null Model			0.72	435.07
Fixed Model	3.41	3	0.71	437.67
Concreteness				
	$\chi2$	df	R^2	AIC
Null Model			0.49	375.39
Fixed Model	20.41	3	0.48	378.99

$\chi2$ values show the differences between the model in the current row and the model in the previous row.
Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05

4.6.2 Narrativity, Referential Cohesion and Concreteness

The model fit assessment procedure for narrativity, referential cohesion and concreteness indicated that null model was a better fit than the model with Visualization Engagement Percentile as the fixed effect (Table 4-26). Accordingly, no significant effect of Learning Analytics Visualization type on the average quality of messages with regards to these three principal components of Coh-Metrix was observed.

Table 4-27: Analysis of the fixed effects for the model RQ2.1- Post Quality

Deep Cohesion				
Variable	β	SE	95% CI	
			Lower	Upper
Intercept (Low Users)·	-0.240	0.131	-0.503	0.022
Users (Low-Mid Users)	0.124	0.198	-0.273	0.521
Users (Mid-High Users)**	0.668	0.209	0.249	1.087
Users (High Users)**	0.579	0.197	0.184	0.974
Syntactic Simplicity				
Variable	β	SE	95% CI	
			Lower	Upper
Intercept (Low Users)	-0.183	0.197	-0.576	0.210
Users (Low-Mid Users)	0.293	0.201	-0.109	0.694
Users (Mid-High Users)**	0.618	0.205	0.208	1.029
Users (High Users)*	0.454	0.197	0.061	0.849

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, · p<0.1 (marginal)
All variables are on a normal scale

4.7 RQ3: Is there an effect of visualization type on the users' count of posts?

Table 4-28: Variables in RQ3-Quantity

Variable	Description	Type
Predictor Variables		
Learning Analytics Visualization	Experimental condition (The Learning Analytics Visualization user can access)	Categorical
Dependent Variables		
Count of Posts	Total count of Post activity by the user	Continuous

Table 4-12 and Table 4-13 in previous section illustrate Post activity counts (median, 25th and 75th percentile) for Users of each of the three visualizations, as well as Non-Users.

The comparison between the null model and the fixed effects model showed that including the fixed effect of the Learning Analytics Visualization did not result in a model with better goodness-of-fit measures than those of the null model (Table 4-29). Therefore, the mixed-model analysis did not uncover any significant effect of Learning Analytics Visualization type on the users' count of posts.

Table 4-29: Inferential Statistic for Model fit assessment RQ3-Post Count

	χ2	df	R^2	AIC
Null Model			0.74	766.31
Fixed Model	1.23	2	0.70	769.08

χ2 values show the differences between the model in the current row and the model in the previous row.
Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05

4.8 RQ3.1: Is there an effect of visualization type on users' count of posts when controlled for their self-reported Achievement Goal Orientations?

Table 4-30: Variables in RQ3.1-Quantity

Variable	Description	Type
Predictor Variables		
Learning Analytics Visualizations	Experimental condition (The Learning Analytics Visualization participant user can access)	Categorical
Co-variate Variables		
AGO Scale Scores	Participant user's self-reported scores on 6 AGO scale (Task-Approach, Task-Avoidance, Self-Approach, Self-Avoidance, Other-Approach and Other-Avoidance)	Continuous
Dependent Variables		
Count of Posts	Total count of Post activities by the participant user	Continuous

Table 4-31 demonstrates Post activity counts (median, 25th and 75th percentile) for Participant Users of each of the three visualizations. These values are measured per discussion belonging to one of the three courses as explained in 3.6.1.

Table 4-31: Count of Posts for a "Participant User" of each Learning Analytics Visualization

	C1	C2		C3		
	D1	D1	D1	D2	D3	All
Visualization	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)	Mdn(25%,75%)
Class Average	5(4,7)	8.5(7.25,9.75)	N/A	3(3,4)	3.5(2.5,4)	5(4,7)
Top Contributors	6(5,7.25)	5.5(5,6.25)	3(3,3)	5(5,5)	N/A	5(5,6.5)
Quality	5(4,5.75)	6(5.5,6)	4(3,5.25)	3(2,3)	4(3,5)	5(3,6)

According to AIC and likelihood ratio test the fixed model that included the interaction between Learning Analytics Visualization and AGO Scales yielded a significantly better fit than the null model (Table 4-32).The linear mixed-effect analysis

uncovered a significant interaction effect between the Learning Analytics Visualization and other-approach scale scores (F(2,52.98)=4.64, p<0.05)(Further details Table 4-33).

Table 4-32: Inferential Statistic for Model fit assessment RQ3.1-Post Count

	χ2	df	R^2	AIC
Null Model			0.62	183.70
Fixed Model(Visualization*AGO Scales)	40.76**	20	0.89	182.95

χ2 values show the differences between the model in the current row and the model in the previous row.
Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05

Table 4-33: Analysis of the fixed effects for the model RQ3.1-Post Count

Variable	β	SE	95% CI Lower	Upper
Intercept (Class Average)	0.454	0.310	-0.164	1.073
Viz (Top Contributors)	-0.219	0.236	-0.692	0.253
Viz (Quality)·	-0.401	0.217	-0.834	0.033
TaskAp	-0.176	0.181	-0.537	0.186
TaskAv	0.061	0.303	-0.545	0.666
SelfAp	0.394	0.253	-0.112	0.900
SelfAv	-0.155	0.465	-1.085	0.744
OtherAp***	-1.336	0.364	-2.064	-0.607
OtherAv*	1.138	0.438	0.263	2.013
Viz (Top Contributors)*TaskAp	-0.217	0.354	-0.925	0.490
Viz (Top Contributors)*TaskAv	-0.225	0.524	-1.274	0.824
Viz (Top Contributors)* SelfAp	0.904	0.567	-0.229	2.038
Viz (Top Contributors)* SelfAv	-0.917	0.729	-2.375	0.541
Viz (Top Contributors)* OtherAp**	1.339	0.467	0.404	2.274
Viz (Top Contributors)* OtherAv	-0.876	0.609	-2.094	0.341
Viz (Quality)*TaskAp	-0.173	0.240	-0.651	0.306
Viz (Quality)*TaskAv	-0.134	0.377	-0.887	0.618
Viz (Quality)* SelfAp	0.034	0.373	-0.712	0.780
Viz (Quality)* SelfAv	-0.070	0.577	-1.225	1.084
Viz (Quality)* OtherAp*	1.240	0.535	0.171	2.311
Viz (Quality)* OtherAv*	-1.232	0.574	-2.380	0.032

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, · p<0.1 (marginal)
All variables are scaled

Further investigation on the interaction effect between Learning Analytics Visualization and other-approach shows a significant difference in the count of posts between the users of the Class Average visualization and the users of the Top Contributor visualization (z=2.86, p<0.05) and marginally significant difference between the users of the Class Average visualization and the users of the Quality visualization (z=2.32, p<0.1).

4.9 RQ3: Is there an effect of visualization type on the users' quality of posts?

Table 4-34: Variables in RQ3-Quality

Variable	Description	Type
Predictor Variables		
Learning Analytics Visualization	Experimental condition (The Learning Analytics Visualization user can access)	Categorical
Dependent Variables		
Quality of Posts	Average values of the five principal components of Coh-Metrix (Narrativity, Deep Cohesion, Syntactic Simplicity, Referential Cohesion, and Concreteness) for all messages posted by the user that included at least one of the key concepts identified by the instructor	Continuous

Table 4-21 and Table 4-22 in previous section illustrates quality of posts based on Coh-Metrix principal components (median, 25th and 75th percentile) for Users of each of the three visualizations, as well as Non-Users.

4.9.1 Narrativity

According to AIC and the likelihood ratio test the fixed effect model yielded a significantly better fit than the null model (Table 4-35). Further, the linear mixed-effect analysis revealed a significant main effect for Learning Analytics Visualization type on narrativity component, $F(2, 127.85)= 6.55$, $p<0.01$ (Further details Table 4-36).

This effect was probed further by exploring pairwise comparisons. Accordingly, the users of the Class Average visualization had significantly lower scores of narrativity than both the users of Top Contributors ($t(141.6)=-2.87$, $p<0.01$, 95% CI [-0.88, -0.16]) and Quality visualizations ($t(86.7)=-3.18$, $p<0.01$, 95% CI [-0.91, -0.21]).

4.9.2 Deep Cohesion, Syntactic Simplicity, Referential Cohesion and Concreteness

The model fit assessment procedure for deep cohesion, syntactic simplicity and referential cohesion and concreteness indicated that null model was a better fit than the model with Learning Analytics Visualization as the fixed effect (Table 4-35). Accordingly, no significant effect of Learning Analytics Visualization type on the average quality of messages with regards to these four principal components of Coh-Metrix was observed.

Table 4-35: Inferential Statistic for Model fit assessment RQ3-Post Quality

Narrativity				
	χ2	df	R^2	AIC
Null Model			0.59	444.18
Fixed Model	9.89**	2	0.80	438.29
Deep Cohesion				
	χ2	df	R^2	AIC
Null Model			0.27	444.82
Fixed Model	5.44·	2	0.30	443.38
Syntactic Simplicity				
	χ2	df	R^2	AIC
Null Model			0.08	433.48
Fixed Model	1.04	2	0.09	436.43
Referential Cohesion				
	χ2	df	R^2	AIC
Null Model			0.72	435.07
Fixed Model	1.95	2	0.65	437.12
Concreteness				
	χ2	df	R^2	AIC
Null Model			0.49	375.39
Fixed Model	0.76	2	0.45	378.64

χ2 values show the differences between the model in the current row and the model in the previous row.

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05

Table 4-36: Analysis of the fixed effects for the model RQ2.1- Post Quality

Narrativity				
Variable	β	SE	95% CI Lower	Upper
Intercept (Class Average)	-0.390	0.212	-0.814	0.033
Viz (Top Contributors)**	0.521	0.182	0.157	0.884
Viz (Quality)**	0.600	0.176	0.208	0.912

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, · p<0.1 (marginal)

All variables are on a normal scale

4.10 RQ3.1: Is there an effect of visualization type on users' quality of posts when controlled for their self-reported Achievement Goal Orientations?

Table 4-37: Variables in RQ3.1-Quality

Variable	Description	Type
Predictor Variables		
Learning Analytics Visualizations	Experimental condition (The Learning Analytics Visualization participant user can access	Categorical
Co-variate Variables		
AGO Scale Scores	Participant user's self-reported scores on 6 AGO scale (Task-Approach, Task-Avoidance, Self-Approach, Self-Avoidance, Other-Approach and Other-Avoidance)	Continuous
Dependent Variables		
Quality of Posts	Average values of the five principal components of Coh-Metrix (Narrativity, Deep Cohesion, Syntactic Simplicity, Referential Cohesion, and Concreteness) for all messages posted by the participant user that included at least one of the key concepts identified by the instructor	Continuous

Table 4-38 demonstrates quality of posts based on Coh-Metrix principal components (median, 25th and 75th percentile) for Participant Users of each of the three visualizations. These values are measured per discussion belonging to one of the three courses as explained in 3.6.1.

Table 4-38: Average Quality of Posts for a "Participant User" of each Learning Analytics Visualization

	C1	C2	C3			
Visualization	D1 Mdn(25%,75%)	D1 Mdn(25%,75%)	D1 Mdn(25%,75%)	D2 Mdn(25%,75%)	D3 Mdn(25%,75%)	All Mdn(25%,75%)
			Narrativity			
Class Average	60.93(45.12,66.13)	63.11(49.06,79.66)	N/A	23.88(23.24,31.74)	24.19(17.35,31.58)	47.09(30.72,64.56)
Top Contributors Quality	67.07(28.87,79.25)	40.91(40.52,52.39)	55.25(42.13,68.37)	35.91(35.91,35.91)	N/A	61.13(36.90,79.36)
	67.06(64.94,70.26)	65.47(62.77,66.81)	47.48(40.51,52.50)	39.61(35.29,52.76)	45.31(42.03,54.07)	62.82(45.31,66.82)
			Deep Cohesion			
Class Average	78.51(59.09,92.49)	68.45(54.42,75.68)	N/A	42.49(31.75,54.55)	65.66(58.13,75.94)	72.22(52.78,87.43)
Top Contributors Quality	73.78(30.71,86.96)	67.99(65.75,73.03)	83.67(81.77,85.57)	53.15(53.15,53.15)	N/A	73.15(61.75,83.36)
	79.71(64.58,93.72)	61.15(51.231,73.18)	68.62(59.89,74.88)	47.52(34.65,73.73)	63.20(49.08,77.88)	70.14(47.52,87.63)
			Syntactic Simplicity			
Class Average	35.71(18.33,46.56)	16.54(10.96,25.41)	N/A	28.16(27.24,45.54)	52.75(47.16,61.23)	31.14(18.89,47.77)
Top Contributors Quality	20.33(7.77,40.71)	18.08(13.51,25.42)	25.73(23.55,27.90)	48.20(48.20,48.20)	N/A	20.85(15.76,41.13)
	22.26(17.08,36.25)	24.91(15.96,35.83)	38.53(31.25,46.23)	29.45(26.18,35.17)	25.23(17.96,31.86)	25.22(19.67,40.90)
			Referential Cohesion			
Class Average	64.15(40.96,70.89)	63.70(55.67,75.40)	N/A	42.89(30.87,60.82)	37.66(28.62,42.34)	59.80(32.49,67.87)
Top Contributors Quality	84.85(26.14,88.66)	63.14(51.32,75.24)	52.22(47.72,56.73)	15.06(15.06,15.06)	N/A	65.93(39.57,88.08)
	70.04(60.44,89.06)	52.62(48.57,55.48)	18.41(13.41,21.78)	41.06(40.21,49.61)	34.14(32.05,51.38)	52.62(34.14,66.62)
			Concreteness			
Class Average	44.62(28.14,62.58)	72.41(68.17,76.30)	N/A	21.10(19.82,47.99)	49.83(43.36,58.03)	51.31(29.75,68.31)
Top Contributors Quality	38.89(11.09,55.15)	72.64(65.87,81.11)	22.48(12.38,32.57)	33.68(33.68,33.68)	N/A	43.94(23.79,62.41)
	54.12(44.56,60.94)	72.35(71.11,78.72)	18.94(13.56,23.44)	13.56(10.82,30.51)	36.24(33.45,42.04)	47.47(27.19,59.52)

For 4 out of 5 principal components of Coh-Metrix (Narrativity, Deep Cohesion, Referential Cohesion, and Concreteness), fixed effect models that included interaction between Learning Analytics Visualization and the 6 AGO Scales resulted with better overall goodness of fit measures (AIC, likelihood ratio test and R^2) than null models (Table 4-39).

Table 4-39: Inferential Statistic for Model fit assessment RQ3.1-Post Quality

Narrativity				
	χ2	df	R^2	AIC
Null Model			0.51	204.99
Fixed Model (Visualization*AGO Scales)	76.11***	20	0.68	168.88
Deep Cohesion				
	χ2	df	R^2	AIC
Null Model			0.33	199.92
Fixed Model (Visualization*AGO Scales)	67.16***	20	0.59	172.76
Syntactic Simplicity				
	χ2	df	R^2	AIC
Null Model			0.14	194.58
Fixed Model Model (Visualization+AGO Scales)	23.25**	8	0.23	187.33
Referential Cohesion				
	χ2	df	R^2	AIC
Null Model			0.69	200.31
Fixed Model(Visualization*AGO Scales)	51.98***	20	0.78	188.33
Concreteness				
	χ2	df	R^2	AIC
Null Model			0.47	178.24
Fixed Model(Visualization*AGO Scales)	47.22***	20	0.74	171.02

χ2 values show the differences between the model in the current row and the model in the previous row.
Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05

4.10.1 Narrativity

The linear mixed model for narrativity further revealed significant interaction effect between Learning Analytics Visualization and task-approach ($F(2,63.88)=10.66$, $p<0.001$), Learning Analytics Visualization and task-avoidance ($F(2,63.71)=8.77$, $p<0.001$), and Learning Analytics Visualization and self-avoidance ($F(2,63.81)=5.98$, $p<0.01$). Also, the interaction between Learning Analytics Visualization and other-avoidance was marginally significant ($F(2,63.89)=2.49$, $p<0.1$) (Further details in Table 4-40).

Table 4-40: Analysis of the fixed effects for the model RQ3.1-Narratity

Narrativity				
Variable	β	SE	95% CI	
			Lower	Upper
Intercept (Class Average)	-0.176	0.249	-0.675	0.323
Viz (Top Contributors)**	0.671	0.202	0.266	1.075
Viz (Quality)*	0.480	0.189	0.103	0.859
TaskAp	-0.015	0.157	-0.330	0.300
TaskAv·	0.519	0.275	-0.031	1.068
SelfAp	0.065	0.217	-0.368	0.498
SelfAv	-0.561	0.429	-1.419	0.296
OtherAp·	-0.614	0.325	-1.263	0.035
OtherAv*	1.021	0.403	0.214	1.828
Viz (Top Contributors)*TaskAp***	1.456	0.320	0.816	2.096
Viz (Top Contributors)*TaskAv*	0.938	0.462	0.013	1.863
Viz (Top Contributors)* SelfAp	-0.795	0.653	-2.102	0.512
Viz (Top Contributors)* SelfAv·	-1.331	0.741	-2.813	0.152
Viz (Top Contributors)* OtherAp	0.105	0.412	-0.929	0.718
Viz (Top Contributors)* OtherAv	-0.501	0.544	-1.588	0.587
Viz (Quality)*TaskAp	0.136	0.248	-0.360	0.632
Viz (Quality)*TaskAv*	-0.767	0.338	-1.443	-0.091
Viz (Quality)* SelfAp·	-0.588	0.345	-1.279	0.102
Viz (Quality)* SelfAv·	0.958	0.522	-0.087	2.002
Viz (Quality)* OtherAp	0.414	0.448	-0.481	1.310
Viz (Quality)* OtherAv*	-1.114	0.510	-2.135	-0.094

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, . p<0.1 (marginal)
All variables are scaled

Further investigation on interaction effect between Learning Analytics Visualization and task-approach showed a significant difference between the scores of narrativity of the users of the Top Contributors visualization compared to the scores of narrativity of the users of the Quality visualization (z=-3.84, p<0.001) and between the scores of narrativity of the Class Average visualization and those of the users of Top Contributors (z=4.55, p<0.001). The positive association between the task-approach scale and narrativity scores was largest for Top Contributors, followed by the positive association for the users of the Quality visualization, while a negative association was found for the users of the Class Average visualization.

Probing the Interaction effect between Learning Analytics Visualization and task-avoidance showed a significant difference in narrativity scores between the users of Top Contributors compared to the users Quality (z=-4.02, p<0.001) and marginally significant

difference between the users of the Class Average and Quality visualizations ($z=-2.27$, $p<0.1$). The effect of task-avoidance was negative on narrativity for the users of the Quality visualization, while this effect was positive on the narrativity scores of the users of the other two visualizations.

Further analysis exploring the interaction effect between Learning Analytics Visualization and self-avoidance goal-orientation exhibits significant difference in the scores of narrativity between the users of the Top Contributors and the Quality visualization ($z=3.32$, $p<0.01$). Self-avoidance scale scores were positively associated with narrativity scores for the users of the Quality visualization, whereas these scores were negatively associated with narrativity scores of the users of both Top Contributors and Class Average visualizations.

4.10.2 Deep Cohesion

As for the deep cohesion model, significant interaction effects between Learning Analytics Visualization and task-approach ($F(2,64.86)=12.58$, $p<0.001$), Learning Analytics Visualization and task-avoidance ($F(2,64.73)=5.34$, $p<0.01$), Learning Analytics Visualization and self-avoidance scales ($F(2,65.04)=9.63$, $p<0.001$), and Learning Analytics Visualization and other-avoidance ($F(2,64.48)=6.34$, $p<0.01$) were observed. Also, the interaction between Learning Analytics Visualization and other-approach was marginally significant ($F(2,60.77)=2.83$, $p<0.1$) (Further details in Table 4-41).

Further investigation on the interaction effect between Learning Analytics Visualization and task-approach showed a significant difference in the deep cohesion scores between the users of the Class Average visualization compared to the deep cohesions scores of the users of the Top Contributors visualization ($z=4.68$, $p<0.001$), and between deep cohesions scores of the users of the Top Contributors and those of the Quality visualizations ($z=-4.62$, $p<0.001$). The positive association between task-approach scales and deep cohesion was largest for the Top Contributors, while much smaller positive association was found for the Quality visualization followed by the association for the users of the Class Average visualization.

Table 4-41: Analysis of the fixed effects for the model RQ3.1-Deep Cohesion

Deep Cohesion				
Variable	β	SE	95% CI	
			Lower	Upper
Intercept (Class Average)	0.244	0.170	-0.095	0.584
Viz (Top Contributors)	0.152	0.214	-0.276	0.580
Viz (Quality)	-0.170	0.198	-0.566	0.226
TaskAp	0.077	0.166	-0.256	0.409
TaskAv*	0.712	0.290	0.131	1.293
SelfAp	-0.121	0.227	-0.576	0.333
SelfAv*	-0.902	0.448	-1.799	-0.005
OtherAp*	-0.770	0.338	-1.446	-0.095
OtherAv*	1.073	0.423	0.226	1.920
Viz (Top Contributors)*TaskAp***	1.579	0.337	0.905	2.253
Viz (Top Contributors)*TaskAv	-0.433	0.487	-1.407	0.541
Viz (Top Contributors)* SelfAp	-0.373	0.689	-1.751	1.004
Viz (Top Contributors)* SelfAv	-0.837	0.779	-2.396	0.722
Viz (Top Contributors)* OtherAp	-0.064	0.434	-0.933	0.805
Viz (Top Contributors)* OtherAv	-0.237	0.574	-1.385	0.912
Viz (Quality)*TaskAp	-0.073	0.259	-0.591	0.446
Viz (Quality)*TaskAv**	-1.130	0.355	-1.840	-0.420
Viz (Quality)* SelfAp	-0.081	0.363	-0.806	0.644
Viz (Quality)* SelfAv**	1.803	0.548	0.707	2.899
Viz (Quality)* OtherAp.	0.844	0.454	-0.064	1.752
Viz (Quality)* OtherAv**	-1.639	0.529	-2.696	-0.581

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, . p<0.1 (marginal)

All variables are scaled

Probing the Interaction effect between Learning Analytics Visualization and task-avoidance showed significant difference in the scores of deep cohesion of the messages posted by the users of the Class Average and Quality visualizations (z=-3.18, p<0.01). The task-avoidance showed a negative effect on deep cohesion for the users of the Quality visualization, while this effect on deep cohesion was positive for the users of the other two visualizations.

Further exploration on the interaction effect between Learning Analytics Visualization and self-avoidance exhibited a significant difference in the scores of deep cohesion between the Class Average visualization users and the Quality visualization users (z=3.29, p<0.01), and between the Top Contributor visualization users and the Quality visualization users (z=3.67, p<0.001). Self-avoidance scale scores were positively associated with deep cohesion scores for the users of the Quality visualization, whereas this self-avoidance scale scores were negatively associated with the deep cohesion

scores for the messages posted by the users of the Top Contributors and the Class Average visualization.

Further investigation on interaction effect between Learning Analytics Visualization and other-avoidance showed a significant difference in the scores of deep cohesion between the users of the Top Contributors visualization compared to those of the users of the Quality visualization ($z=-2.79$, $p<0.05$) and between the users of Class Average visualization and the Quality visualization users ($z=-3.10$, $p<0.01$). The association between other-avoidance scale scores and deep cohesion scores was negative for the users of the Quality visualization, while the association was positive for the users of both Top Contributors and Class Average visualizations.

4.10.3 Referential Cohesion

Analysis of mixed models for referential cohesion revealed a significant interaction effect between Learning Analytics Visualization and task-approach scales ($F(2,63.58)=9.86$, $p<0.001$) (Further details inTable 4-42).

Further investigation of the interaction effect between Learning Analytics Visualization and task-approach showed a significant difference in the scores of referential cohesion between the users of the Top Contributor visualization and the users of the Quality visualization ($z=-3.75$, $p<0.001$), and between the Class Average visualizations users and Top Contributor users ($z=4.39$,$p<0.001$). The association between the task-approach scale scores and referential cohesion scores was positive for the users of the Top Contributors visualization, while negative association between the task-approach scale scores and the referential cohesion scores was found for the users of both Quality and Class Average visualizations.

Table 4-42: Analysis of the fixed effects for the model RQ3.1-Referential Cohesion

Referential Cohesion				
Variable	β	SE	95% CI	
			Lower	Upper
Intercept (Class Average)	-0.037	0.312	-0.661	0.587
Viz (Top Contributors)*	0.624	0.242	0.141	1.107
Viz (Quality)	0.229	0.223	-0.217	0.675
TaskAp	-0.285	0.191	-0.667	0.098
TaskAv	0.236	0.329	-0.635	0.682
SelfAp**	0.713	0.260	0.193	1.232
SelfAv	-0.067	0.516	-1.100	0.965
OtherAp	0.020	0.389	-0.759	0.798
OtherAv	-0.213	0.490	-1.193	0.767
Viz (Top Contributors)*TaskAp***	1.677	0.382	0.914	2.441
Viz (Top Contributors)*TaskAv	0.469	0.551	-0.634	1.571
Viz (Top Contributors)* SelfAp	-1.169	0.775	-2.718	0.381
Viz (Top Contributors)* SelfAv·	-1.609	0.878	-3.365	0.147
Viz (Top Contributors)* OtherAp	-0.802	0.491	-1.785	0.181
Viz (Top Contributors)* OtherAv	0.727	0.655	-0.583	2.037
Viz (Quality)*TaskAp	0.159	0.275	-0.304	0.709
Viz (Quality)*TaskAv	0.208	0.406	-0.925	1.021
Viz (Quality)* SelfAp	-0.582	0.398	-1.757	0.214
Viz (Quality)* SelfAv	-0.011	0.628	-1.507	1.244
Viz (Quality)* OtherAp	0.093	0.548	-0.745	1.190
Viz (Quality)* OtherAv	0.393	0.614	-1.449	1.621

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, . p<0.1 (marginal)

All variables are scaled

4.10.4 Concreteness

Further analysis of the models for concreteness uncovered a significant interaction between Learning Analytics Visualization and task-approach ($F(2,63.17)=3.42$, $p<0.05$), Learning Analytics Visualization and task-avoidance ($F(2,63.15)=3.92$. $p<0.05$), and Learning Analytics Visualization and other-avoidance ($F(2,63.24)=4.17$, $p<0.05$). In addition, the analysis showed a marginally significant interaction effect between Learning Analytics Visualization and self-avoidance scales ($F(2.63.17)=2.99$, $p<0.1$), as well as between Learning Analytics Visualization and other-approach ($F(2,63.68)=3.03$, $p<0.1$) (Further details in Table 4-43).

Further investigation of the interaction effect between Learning Analytics Visualization and task-approach showed a significant difference in the concreteness scores between users of the Top Contributor visualization and the Quality visualization

(z=-2.46, p<0.05) and between the Class Average visualization users and the Top Contributor visualization users (z=2.39, p<0.05). The task-approach scale association with concreteness scores was positive and largest for the users of the Top Contributors visualization, followed by the positive association for the Class average visualization users, while a negative association was found for the users of the Quality visualization.

Table 4-43: Analysis of the fixed effects for the model RQ3.1-Concreteness

Concreteness				
Variable	β	SE	95% CI	
			Lower	Upper
Intercept (Class Average)	0.361	0.478	-0.595	1.317
Viz (Top Contributors)	-0.133	0.199	-0.531	0.264
Viz (Quality)	-0.022	0.186	-0.394	0.350
TaskAp	0.042	0.154	-0.267	0.351
TaskAv	-0.429	0.270	-0.970	0.111
SelfAp	0.137	0.214	-0.290	0.564
SelfAv	0.524	0.424	-0.323	1.372
OtherAp*	0.701	0.321	0.058	1.344
OtherAv**	-1.074	0.398	-1.869	-0.278
Viz (Top Contributors)*TaskAp*	0.754	0.315	0.124	1.385
Viz (Top Contributors)*TaskAv	-0.399	0.455	-1.310	0.512
Viz (Top Contributors)* SelfAp	0.158	0.643	-1.129	1.444
Viz (Top Contributors)* SelfAv*	-1.730	0.730	-3.191	-0.270
Viz (Top Contributors)* OtherAp*	-0.986	0.405	-1.779	-0.178
Viz (Top Contributors)* OtherAv**	1.425	0.535	0.356	2.495
Viz (Quality)*TaskAp	-0.082	0.245	-0.573	0.409
Viz (Quality)*TaskAv·	0.648	0.333	-0.019	1.314
Viz (Quality)* SelfAp	0.183	0.340	-0.498	0.864
Viz (Quality)* SelfAv	-0.826	0.516	-1.857	0.206
Viz (Quality)* OtherAp	-0.734	0.449	-1.632	0.164
Viz (Quality)* OtherAv*	1.249	0.506	0.236	2.260

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, . p<0.1 (marginal)
All variables are scaled

Probing the Interaction effect between Learning Analytics Visualization and task-avoidance showed a significant difference in the concreteness scores between the users of the Top Contributors visualization and the Quality visualization (z=2.49, p<0.05). Further analysis showed a positive effect on concreteness scores for the Quality visualization users, while this effect was negative on the concreteness scores for the users of the other two visualizations.

Further investigation of the interaction effect between Learning Analytics Visualization and other-avoidance showed a significant difference in the concreteness scores between the users of the Class Average visualization and the users of both Top Contributors ($z=2.66$, $p<0.05$) and Quality visualizations ($z=2.47$, $p<0.05$). The association between other-avoidance scale scores and concreteness scores was negative for the users of the Class Average visualization, while the association was positive for the Top Contributors and Quality visualizations.

4.10.5 Syntactic Simplicity

According to AIC and likelihood ratio test the fixed model that included both Learning Analytics Visualization and AGO scales as fixed effects without the interaction term yielded a better fit than the null model (Table 4-39). Further analysis for syntactic simplicity principal component did not reveal any significant effect of the AGO scale scores or Learning Analytics Visualization types. However, the main effect of visualization type was marginally significant $F(2,62.81)=2.57$, $p<0.1$ (Further details in Table 4-44).

Table 4-44: Analysis of the fixed effects for the model RQ3.1-Syntactic Simplicity

Syntactic Simplicity				
Variable	β	SE	95% CI	
			Lower	Upper
Intercept (Class Average)	0.189	0.218	-0.247	0.624
Viz (Top Contributors)·	-0.483	0.254	-0.990	0.024
Viz (Quality)·	-0.487	0.256	-0.998	0.024
TaskAp	0.081	0.140	-0.200	0.362
TaskAv	-0.082	0.180	-0.443	0.279
SelfAp	-0.005	0.202	-0.409	0.400
SelfAv	-0.250	0.280	-0.808	0.308
OtherAp	-0.067	0.208	-0.482	0.349
OtherAv	-0.001	0.254	-0.508	0.506

Significance codes: *** p<0.001 , ** p<0.01 , *p<0.05, . p<0.1 (marginal)

All variables are scaled

5 Discussion and Conclusions

The overall goal of this study was to investigate how students responded to different Learning Analytics Visualizations. Particularly, how the visualization motivated them to engage with the Visualizations and how using these visualizations affected their posting behavior in online discussions. We also looked at the effects of the visualization use of different facets of Achievement Goal Orientations.

5.1 Interpretation of the results

Using this methodology, we primarily investigated whether the visualization users were associated with different posting behaviors than the non-users. Further, we studied whether those who used the Learning Analytics Visualizations their level of usage influenced their posting behavior. Also we aimed at finding out the effect of different visualizations on students' level of engagement with the Learning Analytics Visualizations and its influence on their posting behavior. Finally, we studied how considering self-reported Achievement Goal Orientations affected the association between different Learning Analytics Visualizations and the above dependent variables.

5.1.1 Students' Engagement with Different Visualizations Considering Their AGOs

Looking at effect of different Learning Analytics Visualizations, mixed model analysis did not show any significant differences between users of different Learning Analytics Visualizations on their level of engagement with the scaffolds. However, adding students' self-reports of their Achievement Goal Orientations to our analysis suggested that regardless of the visualization, AGO scale scores contributed to how much students used the Learning Analytics Visualizations. However, still none of the six AGO scales played a significant role in explaining the engagement level.

5.1.2 Effect of Using Visualizations on Students' Quantity of Posts

When it comes to the effect of visualizations on their posting behavior, the result of hierarchical linear mixed model analysis showed that using these Learning Analytics Visualizations to present information about students' posting in the online group discussions motivated students to increase their contribution level which can be viewed as an adjustment in the learning behavior. Moreover, students who used Learning Analytics Visualizations more extensively had a higher number of posting contributions.

5.1.3 Effect of Using Visualizations on Students' Quality of Posts

With regards to the quality of posted messages, our study showed a prominent role of using Learning Analytics Visualizations on some features of discourse in the discussion postings. Analyzing students' discourse and language features enabled for tracking their cognitive presence or knowledge construction levels, which is otherwise not explicitly expressed. Therefore, Coh-Metrix has been recently used to explore leaners' cognitive processes in the realm of collaborative learning [13].

According to our results intensive users of Learning Analytics Visualizations posted messages that had higher deep cohesion measure and were syntactically simpler than low and average users. The concerns of deep cohesion, which is focused on the situation model level of discourse, goes beyond the explicit connection and overlap between words in the text. In fact, this principal component of Coh-Metrix is enhanced by existence of solid causal, intentional, temporal and spatial connections [31, 32]. Higher levels of deep cohesion show deeper integration of the ideas with background knowledge and fewer conceptual gaps. Also recent findings consistently indicate that individuals and groups who engaged in deeper cohesive integration performed significantly better in the context of collaborative learning in blended courses and MOOCs [14, 15]. So it seems that there is a connection between intensive use of Learning Analytics Visualizations and students' better understanding of the discussion topic concepts and ability to integrate it with their prior knowledge and also the potential to perform well.

Established research shows that complex structures can negatively influence comprehension. However, prior findings about the effect of syntactic simplicity on performance in collaborative learning are mixed. A discourse analysis of discussion

forums in MOOCs shows that students who constructed message with simpler syntactic structures had significantly higher performance [14]. However, similar analysis on the messages exchanged between students through online chat showed that syntax simplicity was negatively associated with individual performance [15]. In the latter case, deep cohesion was positively associated with performance. Therefore, it may be that as a typical side effect of text with high deep cohesion their messages contained more complex syntax structures with high number of words, dense sentences and higher frequency of embedded phrases [32]. Our results illustrate that students who used provided learning analytics visualizations more frequently also achieved higher deep cohesion while avoiding more complex syntactical structure in comparison to those who used it less frequently. Prior research confirms this to be a desirable outcome.

5.1.4 Effect of Different Visualizations on Students' Quantity of Posts Considering their AGOs

Further, we focused only on students who used different Learning Analytics Visualizations. According to the linear mixed models analyses performed, the quantity of contributions in the group discussion was not significantly different between users of different Learning Analytics Visualizations. However, adding self-reported AGO scores as co-variates showed that different Learning Analytics Visualizations can have different effects on students posting behavior when they have different achievement goal orientations.

For students who used Top Contributors visualization, higher scores on other-approach scale were significantly associated with higher numbers of posts, whereas for those who used Class Average or Quality visualization, the association was negative. This could mean that for students who had more orientation towards other-approach goal, Top Contributors visualization could motivate them to contribute more but for the other two visualizations it discouraged them from more contributions. This is in alignment with prior research showing that students with other-approach goals assess their competence level in terms of normative standards and aim at outperforming their peers [16]. In this case, the learners who used the Top Contributors visualization may have interpreted the norm based on the contribution level of those who had the highest number of postings in the class. Another interpretation is that they may have strived to gain visibility by the rest of

the class which means being listed as top contributors themselves. Hence, this positive association between other-approach scale scores and numbers of posts for users of this visualization is not surprising.

For other students with high tendency for the other-approach goal orientation who engaged with Class Average visualization their judgment of peers' performance may have been influenced by the average performance of their class. Research shows that students who adopt normative standards usually rely on instructors criteria as they believe this can best lead to outperforming their peers if no other visible norm exists [58]. In light of this, the instructor's clearly expressed criteria might fade out behind the analytics metrics – based on real-time updates – presented in the visualization. If the class average is below, teachers' expectation at any given time, students with other-approach tendency may have followed that as their normative standards for their goal. Also, previous research shows that normative goal-standards (other-approach) can range from modest to extreme [58]. It might be that learning analytics visualization can be an influencing factor on determining the end points of this range. Top contributors visualization encourages setting a higher standard to outperform in comparison to the class average which means it is more challenging to achieve and requires more effort. This is accordance with the idea in [69] that if desirable participation behaviors are explicitly exposed to students oriented towards performance goals, it can encourage them to engage more productively in the discussion activity. In this study we used the 3×2 AGQ model in which in which Other and Task goals correspond to Performance goals in prior AGO models.

An important implication for intervention design to support use of Learning Analytics in a course is that analytics metrics need to be aligned with teachers' expressed criteria, which also should reflect on how to do well in the task. Top Contributors visualization in this case only focuses on the quantity of contributions by the highest contributors in the class. For a balanced productive engagement quality of contributions which illuminates on the level knowledge construction are equally important.

5.1.5 Effect of Different Visualizations on Students' Quality of Posts Considering their AGOs

In addition, we investigated differences in the quality of contributions for users of different Learning Analytics Visualizations. The analysis did not show any significant

differences between the three visualizations for most of the principal discourse features (i.e., Deep Cohesion, Referential Cohesion, Syntactic Simplicity and Concreteness). An exception was narrativity of the messages, which was revealed to be significantly higher for users of Quality visualization and Top Contributors than Class average users. According to language and discourse literature, narrative genre of discourse and its rhetorical structure expresses objects, events, actions and emotions of characters over time in a particular spatial setting which is typical in everyday oral communication and stories [30]. As opposed to narrative, expository/informational language is decontextualized and is intended to inform about new concepts, facts, and technical matters as in the case of academic papers and textbooks [30]. The genre of a text can be an indicator of its difficulty. For example, narrative text is considerably easier and faster to read, comprehend, and remember than expository/informational text [32]. This is mainly because narrative discourse adopts more familiar and concrete words that only require general knowledge to understand [30]. In contrast, expository texts regularly use more abstract words and less familiar ideas. Accordingly, relevant findings in collaborative learning suggest that students whose discourse is more narrative make better social relationship with others in the discussion forum [14, 35]. Particularly, findings of a study in MOOCs showed that students with a narrative style of writing who also a high maintained level of deep cohesion in their messages managed to build stronger connections [35]. Hence, high narrativity seems to be advantageous for social accomplishments in collaborative learning. This could mean that Quality and Top Contributors were more successful in terms of supporting students to achieve that goal.

A recent study found that students who used more expository language and constructed messages with higher deep cohesion outperformed others with a more narrative style and lower cohesion [15]. Initially, considering narrativity as an independent component, that result was considered counterintuitive based on previous studies. However, accounting for deep cohesion, it can be inferred that maintaining a higher level of deep cohesion compensated for the difficulty of the expository text. It is also known that expository text demands extensive domain knowledge in order to generate the inferences required for comprehension [55]. This could mean that students with a more expository style, as opposed to a narrative style, managed to develop better knowledge and hence made stronger inferences as evident by higher deep cohesion. However, based on our findings users of Top Contributors and Quality visualization who used a more narrative

style also maintained the same level of deep cohesion as users of Class Average who adopted a more expository language. Therefore, it is likely that students who used the Top Contributors and Class Average visualizations can benefit from the advantages of better social connection while maintaining their performance in comparison to Class Average users. Further investigation is required to better understand the connection between discourse components and different aspects of collaborative learning.

Going to the next level and adding self-reported AGO scores as a covariate showed that different Learning Analytics Visualizations can have different effects on students' quality of products in discussions. Particularly, our findings suggest that 4 out 5 principal discourse features observed in their posted messages (i.e., Narrativity, Deep Cohesion, Referential Cohesion, and Concreteness) were associated with the type of visualization students used when controlled for their self-reported AGOs. For each visualization, summary of significant associations are reported in Table 5-1. Positive associations show that higher scores on a specific AGO scale are associated with higher scores on a specific discourse principal component when using a visualization, whereas negative associations indicate higher scores on an AGO scale are associated with lower scores on discourse features for a particular visualization.

Table 5-1 uncovers that significant findings with regards to the effect of visualization type on different discourse features are not homogenous when controlled for different AGO scale sore. This suggests that presentation of different information through Learning Analytics Visualizations to students with different Achievement Goal Orientations may have different association with their quality of message. The quality of messages is observed in terms of multiple discourse features that do not necessarily converge together in each case. Out of the four visible features present, the most highlighted and frequent discourse component is deep cohesion. For long, the importance of cohesion in text and oral communication has been emphasized by cognitive scientists who aimed at understanding how human mind constructs meaning from discourse [13]. In fact, measuring cohesion was the main driver for the development of Coh-Metrix which later expanded to other features. Therefore, in our examples for interpretation of findings in this section we focus on deep cohesion as the main indicator for the quality of messages. There are almost consistent findings in collaborative learning literature showing positive outcomes of deep cohesion. Higher levels of deep cohesion show deeper integration of

the ideas with background knowledge and less conceptual gaps, as well as, better individual and group performance [14, 15].

Table 5-1: Summary of Mixed Model Analysis for Interaction between Learning Analytics Visualization and AGO Scale on Quality of Posts

Predictor Variable		Dependent Variable	Direction of Association
Visualization	AGO Scale		
Class Average	Task-Approach	Narrativity	-
		Deep Cohesion	+
		Referential Cohesion	-
		Concreteness	+
	Task-Avoidance	Narrativity	+
		Deep Cohesion	+
		Concreteness	-
	Self-Avoidance	Narrativity	-
		Deep Cohesion	-
	Other-Avoidance	Deep Cohesion	+
		Concreteness	-
Top Contributors	Task-Approach	Narrativity	+
		Deep Cohesion	+
		Referential Cohesion	+
		Concreteness	+
	Task-Avoidance	Narrativity	+
		Deep Cohesion	+
		Concreteness	-
	Self-Avoidance	Narrativity	-
		Deep Cohesion	-
	Other-Avoidance	Deep Cohesion	+
		Concreteness	+
Quality	Task-Approach	Narrativity	+
		Deep Cohesion	+
		Referential Cohesion	-
		Concereteness	-
	Task-Avoidance	Narrativity	-
		Deep Cohesion	-
		Concreteness	+
	Self-Avoidance	Narrativity	+
		Deep Cohesion	+
	Other-Avoidance	Deep Cohesion	-
		Concreteness	+

A highlighted aspect of the summary table is the stronger presence of negative valence goals. Besides task-approach, all other goal orientations for which significant associations with the discourse features were observed, are avoidance goals. In the literature, avoidance goals – regardless of the competence definition – have mostly been associated with negative outcomes because of their tendency to avoid failure. Low

cognitive engagement [48], high anxiety and feeling of shame, confusion, disorganized study habits, task-disrupting thoughts, help-avoidance, low achievement and interest are among destructive outcomes of performance-avoidance goals [58]. Similar outcomes have been reported for mastery-avoidance goals such as low self-efficacy, high anxiety, disengagement with the task and poor performance [58]. Therefore, providing feedback to help reduce some of the negative aspects of these avoidance goals is desirable in addition to the prevision of the information shown in the learning analytics visualizations.

Our non-homogenous findings for each avoidance goal across different visualizations suggest that using a particular visualization may have resulted in a positive association between that goal and a discourse feature, while another visualization may have led to a negative association for the same achievement goal and the same discourse component. For instance, those with higher tendency towards self-avoidance goals constructed messages with higher deep cohesion when using the Quality visualization but lower deep cohesion when using the Class Average or Top Contributors visualizations. As discussed previously, high deep cohesion is associated with positive outcomes and thus, it is highly desirable [14, 15]. Students with avoidance goals often suffer from the lack of task focus and hence, are more likely to experience low deep cohesion. It seems that the Quality visualization may have played a positive role in directing the students with high self-avoidance goals towards overcoming task disrupting thoughts and integrating more cohesive messages, while the other two visualizations may have played a negative role. A possible explanation is that presentation of information in the Quality visualization was more focused on improvements of *self* over time (keywords coverage is ascending over time) which can increase feeling of self-efficacy and self-confidence, and hence, improve the task focus [58]. There is also evidence that perceived confidence can moderate the relationship between performance approach and performance avoidance goals [42]. Having said that, when it comes to task-avoidance, it is observed that the role of the Quality visualization on constructing messages with deep cohesion appeared to be negative, while the other two visualizations played a positive role on the level of deep cohesion. Perhaps for students with task-avoidance strivings, seeing the concepts they have not covered, increased their stress of doing poorly in the discussions.

As evident in the table, the only goal orientation with a positive valence for which significant findings were observed in terms of the quality of posts was task-approach. Prior

research shows that students with a high task-approach tendency in a particular context compared to others, find the topic interesting, have positive feelings about the task and perceive it as valuable, use deep learning strategies and appreciate both cooperativeness and help seeking [58]. Therefore, it is not surprising that their deep approach to learning can help them mentally connect ideas and construct messages that show stronger signs of deep cohesion [1]. It is interesting that our findings indicate all the three visualization had a positive effect on deep cohesion when controlled for task-approach scores. This finding is not surprising for the Quality visualization, as it directly promotes coherent discussion of some key concepts and logical integration with related ideas. As for Top Contributors, quality may indirectly be promoted through externalization of high standards on the contribution level. Therefore, it may encourage deeper investigation into the topic of discussion. The findings with the Class Average visualization are however counterintuitive. An explanation might be that presence of a real-time positive feedback (seeing that they are better than the average) increased their task-approach goal strivings [59]. Further investigation is required to understand the effect of information presented through visualizations on students with different achievement goals.

5.2 Implications for Theory and Practice

The findings present some methodological, theoretical, and practical implications. As a methodological implication, this study suggests going beyond the measurements of perceived usability and usefulness and highlights the importance of conducting studies in authentic course settings for assessment of Learning Analytics Visualizations. Such empirical studies are required to understand how and to what extent students engage with Learning Analytics Visualizations and evaluate the actual effect of the presented information on students' behaviors and outcomes in online learning activities over the period of a course.

This work also highlights the methodological importance of considering students' individual differences such as motivational constructs in advancing our understanding of the individuals' learning process in connection with the presentation of learning analytics visualizations. Collecting such fine-grained data through self-reported surveys, if combined with other sources of data (e.g., interaction logs and generated artifacts), can

bring the opportunity to identify and study the differences between students in a particular learning context. In the present study, investigating at the level of aggregated data failed to fully uncover the effect of different Learning Analytics Visualizations on students' behavior in online discussions. However, after controlling for individuals' achievement goals, as motivational constructs, effects of different magnitudes and directions were observed. This suggests that not all the students engage and behave the same way in online learning environments. Therefore, in order to have a detailed picture of what particular students do or how they might respond to a treatment, attention towards such theoretical constructs is warranted. It is surprising how little work has been done in the subdomain of Learning Analytics Visualizations that actually focuses on understanding how individual students perceive and respond to the information presented. We hope that this research encourages other investigators to join this endeavor, as we believe it can help research in this direction to continue to develop and mature.

Moreover, it is already known that discourse features add significant improvements in predicting performance and social relations in the context of collaborative learning [13, 14]. However, this work suggests shifting the research on automated linguistic analysis to a deeper level by identifying the potential connection between different discourse components and theoretical constructs such as Achievement Goal Orientation. Present research is an exploratory analysis that shows students with different Achievement Goal Orientations reveal different discourse pattern when assigned to a particular treatment, in this case access to a specific Learning Analytics Visualization. This highlights the rich information that can be obtained from combining deeper linguistic analysis and aptitude constructs when investigating learning-related phenomena where discourse is involved.

In addition, the results pose some important theoretical and practical implications for the use of Learning Analytics dashboards and tools that are theoretically informed and encouraging adoption of effective instructional and interventional practices to support their use. First, our findings confirm the importance of using these dashboards as feedback for students in online learning environments. Particularly our results exhibit a prominent role of Learning Analytics Visualizations on improving participation in online discussions. The Learning Analytics Visualizations were integrated with the discussion activity to prompt a form of intervention with the aim at improving students' participation in online discussions. The instructional design of the discussion activity carefully followed guidelines based on

theories and practices for effective and productive discussion activities (Section 3.3.1). Using such intervention in accordance with teaching and learning practices led to higher average contribution by students, which also increased with the frequency of looking at the visualizations. Also, those who engaged more intensively exhibited higher levels of deep cohesion, while maintaining simple syntactic structures in their messages compared to less intensive users. This indicates that students were able to connect new ideas with background knowledge and overcome conceptual gaps and present those using familiar and simple structures, and thus perform better in discussions [14, 15]. This confirms the potentials of Learning Analytics Visualizations to improve teaching and learning practices if properly integrated into the instructional design of the course and accompanied by proper intervention design to support their use. This is in alignment with prior work in Learning Analytics research suggesting that reporting and visualizing analytics that are easy to understand for the learners and have clear connection with improving their learning processes and outcomes can be very helpful [20]. Also, it confirms the findings of the limited research in this area that reveals learning analytics in the form of dashboards or reports can lead to the change of activities in online discussions that are sometimes intentional and goal-oriented and sometimes unconscious [66].

Second, this research has implications for designing Learning Analytics visualizations. Particularly, it highlights the necessity of designing Learning Analytics dashboards and tools that are theoretically informed to reduce the gap between the two involved disciplines i.e., information design and educational psychology. An initial step in that direction is conducting empirical studies to understand the interaction between complex theoretical constructs and their effects on the learning-related phenomenon. The result of this work strongly suggests consideration of theoretical constructs that underlie individual differences when designing Learning Analytics tools and providing interventions to support their use. Our findings reveal that a particular Learning Analytics Visualization can have different effects on students' behavior in online discussions when they have different achievement goals. The analyses reported in the paper have clearly shown that not all the goal orientations can benefit from a particular Learning Analytics Visualization. For instance, presenting information about the number of covered keywords and logical connection with relevant ideas to students who had tendency towards task-approach goals increased the level of deep cohesion in their messages, which is an indication of better understanding and comprehension of the subject. However, when the same information

was presented to students with task-avoidance goals, they revealed lower deep cohesion in their construction of messages, which indicates a negative effect of the visualization on their learning. Such students when provided with the Top Contributors visualization were encouraged to change their learning practices in a positive way as revealed in their discourse patterns.

This leads to another important and interesting implication of this work. The use of Learning Analytics tools as a feedback mechanism, if designed in consideration with individual differences, can encourage positive changes in students' learning behavior even when they pursue avoidance goals. We know that avoidance goals have been mostly associated with negatives outcomes. Hence, using such personalized and carefully designed interventions can encourage positive changes that may lead to improved learning processes and outcomes. If the feedback provided through these visualizations promotes positive changes such as reducing anxiety and improving feelings of self-efficacy it may even have the potential to direct students towards pursuit of approach goals which according to research have been associated with more positive learning outcomes [58].

Having said that, the Learning Analytics Visualization designed in this research seemed to be less effective on leading students with approach goals to adopt multiple goals. The emerging multiple goal perspective in the research on Achievement Goal Orientation suggests that if students pursue both performance and mastery approach goals at the same time, they can benefit from the positive outcomes associated with each goal [58]. The visualizations used in this research were effective in encouraging or reducing encouragement of the students for pursuing an approach goal (other-approach or task-approach). However, they were less successful in steering students towards learning behaviors expected from alternative approach goals. For instance, students with tendency to other-approach goals are expected to adopt normative standards [16] and it is not surprising that a visualization that presents information about the top contributors in the class motivates them to increase their contributions level in order to outperform their peers. However, we did not observe any positive or negative effect of that visualization on the contribution level of task-approach student. Similarly, students with task-approach tendency are expected to deeply engage and connect ideas with previous knowledge [16]. The analysis revealed that the three presented visualizations encouraged them to

construct messages that had high levels of deep cohesion. However, no positive or negative influence of the visualizations was observed on students with other-approach goals. Overall, our results showed that students with approach goals were firmly following a particular competency. Research on investigating personal factors on the effectiveness of Learning Analytics visualizations is at its early stages and more empirical studies are required to offer actionable suggestions for improvements of Learning Analytics designs that could be suitable for individuals that exhibit different characteristics based on theoretical constructs in educational psychology.

Third, our findings suggest moving away from the conventional metrics (e.g., frequencies and class average measures) when designing Learning Analytics dashboards. In this study, we used latent semantic analysis, a natural language processing technique, to capture the quality of the content generated by students at the semantic level. This could uncover a deeper level of knowledge construction. In another visualization, we provided information about the quantity of postings of the top contributors in the class that could promote quality through social comparison. Our findings showed the latter two visualizations were associated with more positive changes on students' participation than the conventional dashboards that shows the average contribution of the class. This is in alignment with a prior research showing that students whose overall goal were high achievement, seeing class average led them to misinterpret that they were doing well because of being slightly above the average [11]. Some students have reported that the class average comparison increased their stress level [66].

5.3 Limitations and Future Work

The current work has several limitations, primarily related to how Learning Analytics Dashboards were integrated into the LMS. Due to constraints on integration of external tools in the Learning Management System, we could not have the visualizations displayed directly on the group discussion page. Therefore, we had to provide it as a link that required additional effort and motivation on students' part to click and be directed to the visualization. We acknowledge that this limitation may have affected the result of the study. Many of the students who did not view the visualization at all may have responded differently if the visualization was directly present on the discussion page. Future work

should explore other integration options and their influence on the adoption and engagement with the tool.

In this study, we considered Achievement Goal Orientation, a theoretical construct that could reveal individual differences with respect to motivational factors in educational context. However, other aptitude constructs that illuminate on students' preferred approaches to learning [5] and use of learning strategies [24] can also help understand how particular students interact with Learning Analytics Visualizations and how those visualizations affect their learning behaviors. In future research we will examine such constructs.

Students' self-reports of their Achievement Goal Orientations through close-ended questionnaires are not necessarily accurate. Very often responses are influenced by cognitive illusions, such as prior experience, and are not tuned to the learning task at hand [6]. Although it seems that overall students show stronger evidence of goal stability than goal shift, aptitudes in general and motivation in particular can change over the longer course of an experiment. Questionnaires fail to capture such temporal shifts [65]. In addition, 6% of participants directly commented that they found all the questions to repeat the same idea. They expressed this through comments such as “It seemed as if it was the same idea rephrased several times…”, “I doubt my English level is degrading because I read lots of same questions” and “They were very repetitive…”. It seems that they did not quite understand the nuanced language adopted in this standard questionnaire. Further work should consider alternative measures of aptitudes such as the trace data-based measures of Achievement Goal Orientation as introduced by [77].

In this study, we did not collect post-study usability and usefulness questionnaires from the participants. Even though these questionnaires are not sufficient to evaluate effectiveness of the visualizations on students’ learning behavior and performance, they still provide a valuable insight on students experience with these visualizations that can serve as a complementary source of data in our future analysis and suggestions for directions for further improvements of the visualizations. Therefore, in our future studies, we intend to ask students to provide feedback on the ease of learning and ease of use of the visualizations, clarity and comprehensiveness of analytics presented, as well as, the perceived value and usefulness of for their learning and its potential effects on their performance.

As for the analytics measures, in this work we only focused on quantity and quality of students' speaking behaviors i.e., ability to express ideas. However, recent research shows that another important prerequisite of having a productive discussion is carefully attending to the posts contributed by others [69]. These listening behaviors that make up around 75% of the time spent in online discussion, have been overlooked until recent endeavors have lighted up on them and different patterns of reading behaviors in online discussions have been identified [68, 69]. Listening behaviors are less visible and harder to track and monitor for students. Therefore, providing learning analytics measures about the depth and diversity of reading different posts can help increase productive engagement. A preliminary study showed that introducing a metric on the percentage of posts read resulted increase in the reading of posts and reducing the gap between posting and listening behaviors [66]. In the future design of analytics dashboards for online discussions we should considers analytics metrics that reflect on reading behaviors and study their effects on students' overall learning and performance in the discussions. It is also interesting to take into account individual differences when doing such analysis.

All the courses in this study had additional instructions guiding students how to effectively participate in online discussions. Previous research clearly indicates that instructional scaffolds can produce desirable effects on development of critical thinking [26]. From this arises the question whether the quality of instructional design moderates the association between visualization use and the quantity and quality of participations in discussions. Accordingly, further research should investigate if the positive association between engaging with the visualizations and posting behaviors would still remain if such level of guidance on effective participations is not available.

In the present work, we provided students with Learning Analytics Visualizations of their participation in the discussion activity. Providing Learning Analytics in online discussions can play a more prominent constructive role for both individual and collective learning if accompanied with a properly designed pedagogical intervention to fully support their use [70]. An intervention should unfold how to systematically integrate analytics to fit with the rest of learning and teaching practices, when and how to present analytics and finally, how to use and develop understanding of them. According to a suggested framework [70], students have to be guided to engage in three main processes when using Learning Analytics Visualizations and reports: grounding, goal-setting, and reflection. As

for grounding, it is emphasized that students need to understand the benefit of the learning activity (in this case discussions) and expectations for doing well which goes back to proper design of the activity. In this regard, we thoroughly considered guidelines for effective design and facilitation of productive discussions [54, 74, 76]. Moreover, students need to understand the connection between the provided Learning Analytics and the leaning activity expectations. This work implicitly addressed this matter by selecting analytics metrics that are relevant to the learning activity expectations specified in the activity description. Additional research attention in the future can be paid towards formulating a more explicit connection between the two. In addition, students can benefit from guidance on self-setting proper goals to attain. Research shows that these goals can encourage learners to put higher effort and monitor their achievement regularly. Once these goals are set, students need to be guided to reflect on them by looking back at the activity description, monitoring their interaction and using the analytics feedback [70]. To support and encourage goal-setting and reflection processes instructors can ask students to set a goal at the beginning of the discussion activity on what they want to accomplish and suggest that students articulate their thoughts in a journal, blog or wiki [72]. As an extension to our current work, we can investigate the effect of a solid pedagogical intervention design around the use of learning analytics. For instance, we can encourage goal-setting and reflection processes and operationalize them by embedding a space around the visualization for students to set their goals and write a reflection journal and have it appear every time they view the visualizations.

Last but not least, these findings may not be generalizable to other courses with different subject domain, structure and settings. This study examined effects of using Learning Analytics Visualizations in online discussions of undergraduate level blended courses in the domain of interactive arts and technology. Therefore, it would be prudent to undertake larger scale studies in other subject domains to confirm and compare the findings.

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