Associations Between Students' Approaches to Learning and Learning Analytics Visualizations

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ABSTRACT
We investigated the connection between Students' Approaches to Learning and different information presented in learning analytics visualizations. Students' approaches to learning are a construct studied in educational psychology. They are context dependent and can be either surface or deep. In a field experiment, we discovered a significant interaction effect between learning analytics visualizations and students' approach to learning on the quality of messages posted by students. The associations were both positive and negative, depending on the combination of information presented in the visualizations and students' approach to learning. The paper contributes to the development of the body of research knowledge that aims to explain of how aptitude constructs from educational psychology interact with learning analytics visualizations.

Categories and Subject Descriptors
K.3.1[Computers and Education] Distance Learning

General Terms
Human Factors, Measurement.

Keywords
Learning Analytics, Individual Differences, Students' Approaches to Learning, Visualizations, Dashboards, Online Discussions

1. INTRODUCTION
One of the envisioned uses of learning analytics tools is to support students' learning, particularly in higher education [16]. This work is positioned in the context of visualizations and dashboards that are used to present learning analytics information to students, with the intent to offer opportunities for awareness, reflection, sense-making and impact on students' learning [25]. The work on Open Learner Models [6], which predates that on LA visualizations, aimed at engaging learners with the information collected by the system with the purpose to provide personalized learning support. Similar to LA Visualization, one direction of independent OLMs added the dimension of supporting student reflection and metacognition in general [5]. Both strands of research share the same purpose: to influence *an individual learner's* decision making, leading to better learning outcomes.

Research on educational psychology shows that individuals differ in their readiness to profit from a particular treatment in a particular context [24]. This indicates the possible varying effect of a treatment for individual students. The work presented here focuses on *individual differences* between learners and aims to determine whether these individual differences relate the varying impact of information presented through visualizations on different aspects of the individual student's learning process and outcome.

In our research we specifically focus on theoretical constructs of aptitudes that can shed light on the observed differences between individuals in learning context (e.g., motivational constructs, epistemic beliefs, approaches to learning, and attitudes) [26].

1.1 Individual differences and learning technology research
Research on the role that individual differences play in the context of learning systems is scarce. Martinez-Miron et al. [18], using an early conceptualization of the achievement goals theory, modulated how help was offered to 9-11 year olds when using a specifically-designed learning environment. No significant correlation was discovered between students' goal orientations and their use of cognitive or motivational strategies. The authors pointed out a methodological problem with the questionnaire they used, i.e. a binary categorization of learners into orientation despite their grouping around the neutral point.

Du Boulay et al. [4] provided a comprehensive proposal for 'Systems that Care' – a framework for intelligent educational systems that considers constructs such as motivation, metacognition and affect. Based on how these constructs are detected, reasoned about and deployed, this work provides an ontology of such systems with several examples of earlier works that demonstrate proposed categories. However, although these early systems incorporate some aptitude constructs into their design, they do not explicitly examine the extent to which students' aptitudes affect their learning outcomes.

In our prior work [22], we have shown that two clusters of students can be identified based on their self-reported approaches to learning in the context of independent research projects and the analysis of trace data shows how the two clusters use different learning strategies. In [23], we have examined the motivational construct of Achievement Goal Orientations [10]. The findings of that work show that quality of the posts in the discussion forums was significantly associated with different types of information presented in LA visualizations (see Section 2.2) when controlled for students' achievement goal orientations.

In this work, we examine another aptitude construct that describes students' preferred approaches to learning within a particular teaching context. The Students' Approaches to Learning [2] instrument measures individual differences using two dimensions: motives and strategies. Surface approach to learning is characterized by fear of failure and is dominated by a narrow target, rote learning, whereas deep approaches have an orientation towards comprehending and sense making with intrinsic motivation [3]. Baeten et al. [1] provide a systematic review of research studying how to encourage deep study approach in user-centered learning environments and identified over forty factors that influence students' approaches to learning. The identified factors, such as students' activity, nature of assessment, and self-direction in learning, are at a higher granularity those examined in our research, i.e. type of information visualized to learners.

1.2 This study

We conducted a field experiment to examine the effects of different types of information presented through learning analytics visualizations on students' learning behavior while controlling for their individual approaches to learning. We designed three learning analytics visualizations where each showed information about a particular aspect of students' participation in online discussions in a university-level blended course. The visualizations were selected in a way to potentially speak to different students' motivations and influence their behavior in the discussion activity. We were explicitly not concerned with designing the visualizations as tools for future continuous use, rather as experimental means to examine if the studied associations exist and to what extent they influence the learning activity.

Asynchronous online discussions are commonly exploited to support collaborative learning [17] and can be seen as an environment in which students can interact to build both collective and individual understanding through conversation with their peers [15]. Critically, the level and quality of students' participation is largely influenced by students' agency [27], regardless of what extent the other learning activities in the course are using learning environment. Additionally, learning analytics in the form of reports and visualizations have been suggested to be supportive of participation and productive engagement in online discussions for the population of students as a whole [28]. Our results confirm that when controlling for students' approaches to learning, different visualizations presented to students are significantly associated with different quality characteristics of posted messages.

2. METHOD

2.1 Study Design and Research Questions

We executed our study as a field experiment in an authentic blended course setting. Students participated in an online group discussion activity on a topic related to the course content. Each student was randomly assigned to an experimental condition, i.e. they had access to one of the three visualizations presenting a particular type of information about their performance in the group discussion activity. Students' approaches to study were measured through a self-reported instrument.

We defined our research questions as follows:

RQ1: *Is there an association between visualization type and the quantity of students' posts when controlled for their self-reported approaches to learning?*

RQ2: *Is there an association between visualization type and the quality of students' posts when controlled for their self-reported approaches to learning?*

2.2 Learning Analytics Visualizations

The choice of learning analytics visualizations was guided by the main goal of our prior study [23], in which we expected that the effect of the visualizations would vary with students' achievement goal orientations. The three visualizations selected aimed to potentially align with different types of motivations underlying students' goals. The achievement goals students have are relatively stable over time [21], as opposed to the students' approaches to learning that are context dependent [3]. Hence, we considered students' goals to be a primary driver for visualization selection in our study. Below are high level descriptions of the three visualizations; for the rationale for their selection readers are referred to

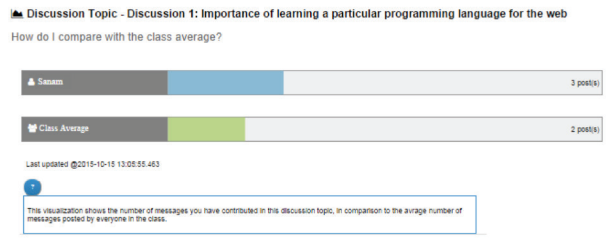

Figure 1: The design of the Class Average visualization

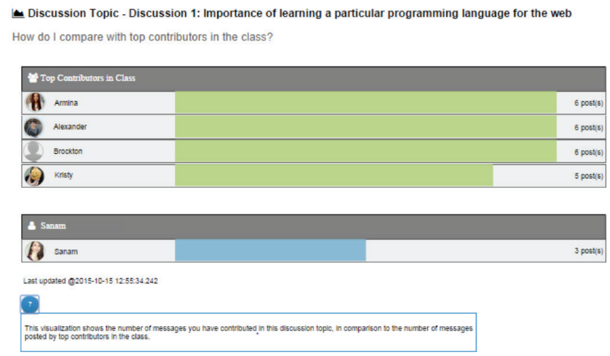

Figure 2: The design of the Top Contributors visualization

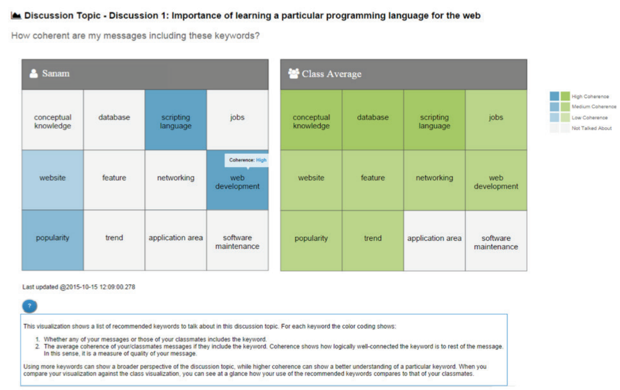

Figure 3: The design of the Quality visualization

[23]. One aspect that is worth repeating here is that each visualization 1) presented one particular metric measuring the performance rather than multiple metrics as is common in more complex dashboards, and 2) provided a different standard for students to gauge their performance.

The *Class Average* visualization has been the most widely used approach when offering learning analytics dashboards and visualizations [7]. It allows students to compare their posting performance with the average number of messages posted by the rest of the class (Figure 1). Students compare their number of postings with that of their fellow students, which may not measure up to the expected number of postings established by an instructor. It has been shown that the effect of class average visualization on students' participation and learning was not always positive [7, 28].

The *Top Contributors* visualization shows the count of messages posted by the student in comparison to the top contributors in the class. Top contributors are the top 5 individuals in the class who have had the highest number of messages posted (Figure 2). The standard here is set to be the best students. This visualization also adds an additional dimension of increased personal recognition in the class by showing student's names and profile pictures.

The *Quality* visualization focuses on the content of posted messages, as opposed to focusing on counts of messages posted. It represents how many of the key concepts the student has covered within his/her posted messages and how well he/she has integrated those with logically related ideas. The key concepts for each discussion topic were previously identified by the course instructor. The visualization (Figure 3) showed the quality for each key concept as a color-coded square. However, the instructor did not identify which concepts are more important or what the visualization should 'look like' for an ideal discussion participation. Rather, students see color intensity as a measure of quality for their messages. One comparison they do have is with the average quality of each concept computed across all posted messages in the class. The color was determined by computing the Latent Semantic Analysis (LSA), a natural language processing technique for measuring the coherence of the text[1], at the sentence level [11].

2.3 Online Group Discussion Activity

LA Visualizations were embedded into a mandatory discussion activity inside Canvas LMS, worth 5% of students' final grade. Discussion across four courses included in the study were designed using the same guidelines that we prepared following collaborative learning literature [19, 30]. The students were in groups of 4-11; the discussions were open for 7-14 days. Each group posted in their own discussion space without the ability to see postings of students outside their group. All students within the same course were given the same open-ended questions and were instructed to explore different aspects of the question and come to the group resolution supported by material taught in the course as well as their individual research. Marking rubric explicitly stated expectations for quality, collaboration, tone, and quantity of the messages per student. LA visualizations were accessible via the link at the top of the discussion page; clicking the link opened a new tab with the visualization for the specific student. A snapshot of the discussion space setup can be viewed at http://at.sfu.ca/gCXQNW (permalink).

2.4 Participants

Participants were students recruited from four courses at the second and third levels in a multidisciplinary Design, Media Arts and Technology program in a Canadian post-secondary institution. All students in the four courses included in the study were randomly assigned to one of the three visualizations. As a result, the students in the same discussion group could be assigned to different visualizations. Both participating and non-participating students engaged in the same discussion activity, and both groups had access to the visualizations. The only difference between participants and non-participants was that those who opted to participate in this study were asked to fill in several questionnaires, including students' approaches to learning questionnaire (see Section 2.5). The participants were predominantly 18-24 years old (93%), both male (66%) and female (34%), with moderate to expert familiarity with online discussions (80%), Canvas LMS (90%) and moderate to expert technical skills (95%).

2.5 Data Collection and Measurement

We retrieved the log data of students' discussion activity from the LMS, including texts of posted messages and the discussion group composition. We integrated this data with recorded visualization views. Finally, we computed counts of posted messages by each student per discussion and counts of visualization views. All the data were time-stamped.

The R-SPQ-2F (Revised Two-Factor Study Process Questionnaire) instrument was used to investigate students' approaches to learning [3] The instrument consists of 20 items that measure two scales (surface and deep approach), which in turn are subdivided into four subscales (deep-motive, deep-strategy, surface-motive, surface-strategy). The responses were recorded on a Likert-type scale, from 1 (never or only rarely true of me) to 5 (Always or almost always true of me). The total scores on 5 items corresponding to a subscale were used as the overall measure on that SPQ subscale.

2.6 Data Analysis

2.6.1 *Coh-Metrix Analyses*

To evaluate the effectiveness of discussions and quality of argumentation we used Coh-Metrix, a computational linguistics facility that measures text characteristics at different levels, such as text coherence, linguistic complexity, characteristics of words and readability [14]. These components explained over 50% of the variability among over 37,250 texts:

- Narrativity: the degree to which the text is a narrative and conveys a story. On the opposite end of the spectrum are expository texts.
- Deep Cohesion: the degree to which the ideas in the text are cohesively connected at a mental and conceptual level.
- Referential Cohesion: reflects the degree to which explicit words and ideas in the text overlap with each other.
- Syntactic Simplicity: reflects the degree to which sentences have a lower number of words and use more simple and familiar structures rather than dense sentences and high frequency of embedded phrases.
- Word Concreteness: the degree to which the text includes words that are concrete and induce mental images in contrast to abstract words.

We computed values for each component above for all student messages that mentioned at least one of the key concepts identified by an instructor. The rationale is based on the work presented in [18], which gauged that these messages have traces of higher level of knowledge construction. For each student we averaged the values for each component in students' retained messages and used the averages as component values in our further analysis.

2.6.2 *Statistical Analysis*

We used hierarchical linear mixed models as a suitable method [20] to reflect the nested structure of our data, i.e. students being embedded in discussion groups, that were part of the discussion topics. To measure the effect of visualizations in our analysis we only included those students who had seen the visualizations at least twice.

For RQ1, the student's count of posts was the dependent variable, with SPQ scores. For RQ2, we identified 5 dependent variables: Narrativity, Deep Cohesion, Referential Cohesion, Syntactic Simplicity, and Word Concreteness. The independent variables in all models for both RQ1 and RQ2 were the visualization type assigned to the student (i.e., Class Average, Top Contributors, or Quality) and the covariates were the scores on four SPQ scales: deep-motive, deep-strategy, surface-motive, and surface-strategy.

We constructed a different linear mixed model for each dependent variable. To select the best fitting model for each dependent vari-

[1] Coherence has been described as "the unifying element of good writing" and hence it can be used in a way to measure quality of text. (http://www.elc.polyu.edu.hk/elsc/material/Writing/coherenc.htm)

able we 1) constructed a *null model* with student within a course as the only random effect[2], 2) built a *fixed model* with the random effects introduced in the null model and the interaction between visualization type and four SPQ scale scores as the fixed effect, and 3) compared the null random-effects only model and fixed-effects model using both Akaike Information Criterion (AIC) and the likelihood ratio test to decide the best fitting model [12]. Primarily, the model with lower AIC was suggested to have a better fit. We used the likelihood ratio test to confirm AIC result. We also calculated an estimate of effect size (R^2) for each model, which reveals the variance explained by the model [29].

3. RESULTS

Because students' use of learning analytics visualizations was voluntary, only a subset of students in the courses opted to view them. In our analysis, we considered only those students who viewed the visualization more than once, which indicated that they returned to the visualization with a purpose to view it, rather than just because of curiosity. Table 1 shows the number of students included in the analyses in RQ1 and RQ2 and how many times they viewed the visualization.

Table 1: Count of visualization views for students who used visualizations

Visualization	N	Median (25%,75%)
Class Average	38	7.00 (4.00, 9.00)
Top Contributors	22	6.50 (3.25, 15.50)
Quality	38	5.00 (3.00, 10.00)

3.1 RQ1

According to the AIC and the likelihood ratio test the fixed model that included the interaction between learning analytics visualization and SPQ scales did not yield better fit than the null model. Hence, we have not discovered any association between the student's number of posts and visualization type when controlling for the student's approach to learning.

3.2 RQ2

For two out of the five Coh-Metrix principal components we used to measure the quality of the messages, namely for Narrativity and Deep Cohesion, the fixed effect models that included interaction between learning analytics visualization and the four SPQ scales resulted in the better overall goodness of fit measures (AIC, likelihood ratio test, and R^2) than the null models (Table 2). In these two cases we proceeded with further analyses.

3.2.1 Narrativity

Table 3 shows the fixed effects model for narrativity. Further examination of the linear mixed model for narrativity revealed the significant interaction effect between learning analytics visualization and *deep-strategy* ($F(2,71.40)=7.68$, $p<0.001$) and between learning analytics visualization and *surface-motive* ($F(2,67.13)=4.03$, $p=0.022$).

Further investigation of the interaction effect between learning analytics visualizations and *deep-strategy* showed a significant difference in change of the scores of narrativity with changing scores of the SPQ Deep Strategy scale of 1) the users of the Top Contributors visualization compared to the users of the Quality visualization ($z=2.83$, $p=0.013$), and 2) the users of the Class Average visualization compared to the users of the Top Contributors

[2] We also considered discussion groups and activity counts as additional levels in the nested structure of the random effects. None yielded a better model.

Table 2. Inferential Statistic for Model fit assessment RQ2

	$\chi2$	df	R^2	AIC
Narrativity				
Null Model			0.46	238.33
Fixed Model	36.607***	14	0.81	229.72
Deep Cohesion				
Null Model			0.34	233.54
Fixed Model	30.456**	14	0.32	231.08

$\chi2$ 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 3: Analysis of the fixed effects for Narrativity

Variable	β	SE	95% CI Lower	95% CI Upper
Intercept (Class Average)	-0.222	0.228	-0.677	0.233
Viz (Top Contributors)	0.203	0.217	-0.231	0.637
Viz (Quality)***	0.688	0.191	0.304	1.072
Deep Motive .	-0.308	0.181	-0.670	0.053
Deep Strategy	0.275	0.202	-0.128	0.678
Surface Motive	-0.201	0.218	-0.636	0.234
Surface Strategy	-0.027	0.184	-0.395	0.342
Viz(TopContr)*Deep Motive	0.511	0.344	-0.177	1.198
Viz(TopContr.)*Deep Strategy***	-1.380	0.357	-2.093	-0.667
Viz(TopContr.)*Surf.Motive*	1.053	0.412	0.230	1.875
Viz(TopContr.)*Surf.Strategy	-0.534	0.400	-1.335	0.266
Viz (Quality)* Deep Motive	0.325	0.286	-0.246	0.897
Viz (Quality)* Deep Strategy	-0.226	0.343	-0.911	0.460
Viz (Quality)* Surf.Motive	-0.109	0.354	-0.817	0.599
Viz (Quality)* Surf.Strategy .	0.264	0.303	-0.342	0.870

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

Table 4: Analysis of the fixed effects model for Deep Cohesion

Variable	β	SE	95% CI Lower	95% CI Upper
Intercept (Class Average)	-0.024	0.147	-0.318	0.270
Viz (Top Contributors)	-0.091	0.228	-0.547	0.364
Viz (Quality)	0.112	0.202	-0.292	0.515
Deep Motive *	-0.384	0.178	-0.740	-0.028
Deep Strategy .	0.370	0.200	-0.029	0.768
Surface Motive .	-0.375	0.216	-0.808	0.057
Surface Strategy	0.150	0.183	-0.216	0.517
Viz(TopContr)*Deep Motive*	0.770	0.341	0.088	1.451
Viz(TopContr.)*Deep Strategy***	-1.278	0.358	-1.996	-0.561
Viz(TopContr.)*Surf.Motive***	1.387	0.412	0.563	2.211
Viz(TopContr.)*Surf.Strategy**	-1.128	0.401	-1.929	-0.327
Viz (Quality)* Deep Motive	0.479	0.294	-0.108	1.066
Viz (Quality)* Deep Strategy	-0.342	0.323	-0.988	0.304
Viz (Quality)* Surf.Motive	0.051	0.332	-0.612	0.714
Viz (Quality)* Surf.Strategy .	0.565	0.295	-0.026	1.156

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

(z=-3.87, p<0.001). The association between the *deep-strategy* and narrativity scores was positive for the Class Average visualization, followed by the small positive association for the users of the Quality visualization, while a strong negative association was found for the users of the Top Contributor visualization (see Table 5 in the discussion section).

The analysis of the interaction effect between learning analytics visualizations and *surface-motive* shows a significant difference in change of the scores of narrativity with changing scores of the SPQ Surface Motive scale of: 1) the users of Top Contributors compared to the users of Quality visualizations (z=-2.62, p=0.023), and 2) the users of the Class Average visualization compared to the users of the Top Contributors visualization (z=2.56, p=0.028). The association between the *surface-motive* and narrativity scores was negative for the Class Average and Quality visualizations, while a strong positive association was found for the users of the Top Contributor visualization (Table 5).

3.2.2 Deep Cohesion

Table 4 shows the fixed effects model for deep cohesion. Significant interaction effects between learning analytics visualization and three SPQ scales were discovered for deep cohesion: 1) *deep-strategy* (F(2,84.97)=6.37, p=0.0026), 2) *surface-motive* (F(2,84.18)=6.23), p=0.003), 3) *surface-strategy* (F(2,3.81)= 7.95, p<0.001). In turn, we further investigated each scale in detail.

First, investigation on the interaction effect between learning analytics visualizations and *deep-strategy* shows a significant difference in change of the scores of deep cohesion with changing scores of SPQ Deep Strategy scale of 1) the users of the Top Contributors visualization compared to the users of the Quality visualization (z=2.40, p=0.043), and 2) the users of the Class Average visualization compared to the users of the Top Contributors visualization (z=-3.56, p=0.001). The positive association between the *deep-strategy* and deep cohesion scores was positive for the Class Average visualization, followed by the small positive association for the users of the Quality visualization, while a strong negative association was found for the users of the Top Contributor visualization (see Table 5 in the discussion section).

Second, the analysis of the interaction effect between learning analytics visualizations and *surface-motive* shows a significant difference in in change of the scores of deep cohesion with changing scores of the SPQ Surface Motive scale of: 1) the users of the Top Contributors visualization compared to the users of the Quality visualization (z=-3.10, p=0.005), and 2) the users of the Class Average visualization compared to the users of the Top Contributors visualization (z=3.37, p=0.002). The association between the *surface-motive* and deep cohesion scores was negative for the Class Average and Quality visualizations, while a strong positive association was found for the users of the Top Contributors visualization (Table 5).

Third, investigation of the interaction effect between learning analytics visualizations and *surface-strategy* shows a significant difference in change of the scores of deep cohesion with changing scores of the SPQ Surface Strategy scale of 1) the users of the Top Contributors visualization compared to the users of the Quality visualization (z=2.40, p=0.043), and 2) the users of the Class Average visualization compared to the users of the Top Contributors visualization (z=-3.56, p=0.001). The association between the *surface-strategy* and deep cohesion scores was strongly positive for the Quality visualization, followed by the positive association for the users of the Class Average visualization, while a strong negative association was found for the users of the Top Contributor visualization (Table 5).

Table 5: Summary of Interactions between Learning Analytics Visualizations and SPQ Scales on Quality of Posts

SPQ Scale	Visualization	Dependent Variable	Assoc. Coeff.
Deep Strategy	Class Average	Narrativity	0.27
		Deep Cohesion	0.37
	Top Contributors	Narrativity	-1.11
		Deep Cohesion	-0.91
	Quality	Narrativity	0.05
		Deep Cohesion	0.03
Surface Motive	Class Average	Narrativity	-0.20
		Deep Cohesion	-0.38
	Top Contributors	Narrativity	0.85
		Deep Cohesion	1.01
	Quality	Narrativity	-0.31
		Deep Cohesion	-0.32
Surface Strategy	Class Average	Deep Cohesion	0.15
	Top Contributors	Deep Cohesion	-0.98
	Quality	Deep Cohesion	0.72

Association coefficients are for scaled variables

4. DISCUSSION AND CONCLUSIONS

The overall goal of this study was to investigate the association between the posting behavior of students with different approaches to learning when presented with different type of information via learning analytics visualizations.

4.1 Interpretation of the results

While our prior work [23] illustrates significant associations between number of posts and the students' other-approach goal orientation for Quality and Top Contributors visualization, no association was discovered with students' approaches to learning. The students with a high tendency towards other-approach goal orientation aimed to compare themselves with others. The surface and deep approaches subscales analyzed in this study focus on how students approach their learning and the criteria established by the instructor. In our case, the marking criteria explicitly specified the minimum number of posts. It appears that no visualization provided enough incentive to modulate the number of posts for either the students with surface approaches (i.e. to do minimum number of posts to meet the criteria) or deep approaches (i.e. focus on discussed concepts).

Our results showed that after controlling for students' approaches to learning, some learning analytics visualizations had positive and some had negative effects on students' quality of posts observed through two discourse features, i.e. Narrativity and Deep Cohesion. Table 5 shows the summary of significant associations for each approach to learning. The values shown in Table 5 are coefficients of change of the discourse feature expressed in standard deviations per one standard deviation change in the student's score in their respective strategy.

Narrativity is a highly robust discourse component [14]. In general, one can find higher narrativity values in the texts conveying a story, using familiar words, showing higher prior knowledge and oral language. In their analysis of K-12 textbooks, Graesser et al. observed that the narrativity z-scores decreased by over one standard deviation from grade level 2 to grade level 11 [14]. This decline was consistent across language used in arts, science and social studies. The opposite of texts with a story are informational texts, usually on unfamiliar topics and in the printed form. In our case the students discussed an unfamiliar topic for which they had to study new material. From this perspective, interpreting our findings is challenging as we are dealing with a new topic situation, delivered in the discussion forum, which resembles more the oral form than the printed one.

It helps to look at the narrativity relative to deep cohesion. As found in [14], “informational texts tend to have higher cohesion between sentences, as compared to narratives; cohesion is apparently one way to compensate for the greater difficulty of unfamiliar subject matter”. *Deep cohesion* measures causal and intentional connections between sentences. In the study by Graesser et al., there was a very small increasing trend observed with increasing grades and at grade 11+ a very small difference between language used in arts, science and social science [14].

Dowell et al. [8] in their group chat study with undergraduate students have shown that increasing deep cohesion and increasing syntactic complexity were strong predictors of the individual students’ learning performance. When evaluating the metrics across all messages within the group, the deep cohesion of all messages in the group was predictive of the group performance. These findings align well with underlying cognitive science theories which emphasize that deep cohesion should be given a higher weight because of its importance for knowledge construction [9].

We observed that for the two subscales which showed significant associations with visualization types, i.e. deep strategy and surface-motive, the change of students’ approaches to learning subscale values had the *same association direction* as the change in narrativity and deep cohesion for *each* of the visualizations. Given the fact that the discussion topics were new, and students’ posts were expected to be expository, we expected to observe that an increase in coherence would be associated with the decrease in narrativity. We observed a similar direction of change in our study when exploring students’ goal orientations [23]. This finding is somewhat contradictory to the previous observations, both by Graesser et al. [14] and Dowell et al. [8], where the deep cohesion compensated for the reduced narrativity. We speculate that the context within which the text was produced, i.e. discussion activity itself, placed a strong demand on communicating ideas in a form that is directed at group members as in oral conversation, i.e. the texts can be easily absorbed and replied to by the group members.

The second notable observation is that of the *rate of change* in narrativity and deep cohesion: it is nearly identical or very close. As can be seen in Table 5 this observation is repeated six times. We do not have any explanation for this observation and it would be interesting to see 1) if this relationship holds in other contexts, and 2) if it does, what are the context characteristics under which the text is produced.

With respect to deep cohesion, our results showed that using a certain visualization showed a positive association between students’ approaches to learning and deep cohesion, while a negative association is observed for a different visualization. The pattern with respect to the *direction* and *value* of the association is observed across the three subscales in Table 5. The associations for both strategy subscales, i.e. deep-strategy and surface-strategy, are nearly a mirror for Class Average and Top Contributor visualizations, when compared with the surface-motive approach. The Quality visualization follows the same pattern in terms of the association direction.

Referring back to Biggs [2], p.11, *deep-strategy* is a meaningful approach, characterized by reading widely and inter-relating with previous knowledge. Our results show that as students’ tendency towards the *deep-strategy* approach increases, we observe a positive association with deep cohesion of 0.37 for the users of the Class Average visualization, a negligible positive association of 0.03 for the Quality visualization and a strong negative association of -0.91 for Top Contributors. Exploring the questionnaire that determines *deep-strategy* [3] may provide a clue why Top Contributors can be detrimental to the students’ performance: the visualization provides no information that can reinforce the student approach, such as encouragement to do more work on a topic, spending extra time to obtain more information, and looking through the most suggested readings. Rather, the visualization drives students’ attention to the highest number of posting per class, detracting from the meaning and focusing on high volume and personal recognition. The Class Average visualization does not support deep approach directly, rather it may be providing a more meaningful norm for quantity of messages and leaving students to concentrate on what is important for their own learning. These suppositions should be tested via more qualitative approaches, such as student think aloud protocols. Interestingly, the association of Quality visualization, which aimed to focus student attention on key concepts to be covered in discussion, resulted in low deep cohesion association with deep-strategy. This may have been because the visualization did not add any new information to deep -strategy learners, since they already are studying broadly and do not need such a direction. Neither are such students interested in a comparison with how others are doing in the class.

The *surface-strategy* approach is reproductive, characterized by students limiting targets to bare essentials and aiming to reproduce material by pursuing rote learning [2], p.11. A high association for deep cohesion for the users of the Quality visualization follows the definition of the *surface-strategy* approach: students pursuing this approach would benefit from an explicit list of key concepts to discuss by pragmatically directing their attention to those concepts. The Top Contributors visualization, highly negatively associated with *surface-strategy* (-0.98), diverts student attention away from one of the main tenets of the approach: minimum essential contribution. From this same perspective, the Class Average visualization is providing information that gives students a reasonable norm to relate to and which does not fundamentally interfere with their approach.

The *surface-motive* approach is defined as instrumental; students’ main purpose of learning is to meet requirements minimally by balancing between working too hard and failing [2]. The interpretation of the observed results is rather difficult. Although one would expect the Class Average visualization to align with this strategy rather well, the association for Deep Cohesion is negative (-0.38). In contrast, there is a highly positive association with the Top Contributors visualization (1.01). One possible explanation may lie in the original Biggs research, which showed one of three factors that loaded on the surface-motive approach was pragmatism (the other two were academic neuroticism and test anxiety). Students showing a high level of pragmatism are grade oriented and they see university as a means to some other end [2]. The Top Contributors visualization, by recognizing the top contributors by name, may appeal to students pursuing the surface-motive strategy as it can potentially elevate them in the eyes of their peers. Exploring connections between students’ approaches to learning and students’ motivations, in the context of the learning analytics visualizations, may help to understand these discovered associations better. Finally, the Quality visualization was negatively associated with Deep Cohesion (-0.32). The Quality visualization in our study showed 16 to 25 key concepts per discussion topic. The relatively large number of key concepts could have caused confusion for students who aimed to do as little work as possible, and aimed only at passing acquaintance with topics [3]. The academic neuroticism factor, defined as “overwhelmed and confused by demands of the course work” [2], p.17 that loaded on this approach would further confirm this interpretation.

It is interesting to note that *deep-motive* approach showed no association with any of the components regardless of the visualization. Deep-motive is intrinsically driven and aims to actualize the interest and competence in a particular academic subject. Hence, since the approaches to learning are context dependent, it may be that the visualizations did not affect students’ intrinsically driven interests in the subjects sufficiently.

4.2 Limitations and Future Research

We are aware of several limitations of our study. Two main limitations related to the way the visualizations were developed and deployed include i) the limited types of information presented, and ii) the need for students to access the visualizations by actively clicking the link. From the theoretical construct point of view, we looked at the students’ approaches to learning in isolation from other ways of measuring individual differences. Even if this research complements our prior study that explored motivational construct of achievement goal orientations [23], further analysis that considers several constructs and their interrelation is needed. Although our data were collected from six discussion activities in four courses, they still originate from the same university program; a validation in a different setting is needed. Finally, this work focused on learning analytics for discussions. Investigating the association between individual characteristics and different ways of visualizing other learning activities is needed to generalize our findings.

Another possible limitation is that students in blended-learning courses do interact in person and they may have also discussed the topic outside of the technology. Although this needs to be acknowledged, we do not see it as likely because i) the groups were randomly generated, hence avoiding established friend circles to form discussion groups, ii) all courses had a major group project that is known to consume much out-of-class time and the grouping is different, and iii) relatively short time of 7-14 days and the number of expected posts per discussion do not work well with logistics when students meet on campus face to face.

The students’ approaches to learning instrument can measure several things, depending on how it is deployed [3]: 1) students’ preferred approaches to learning in a particular context, 2) when applied before and after an intervention, the instrument can measure its effectiveness in bringing students towards deep approaches, and 3) the ratio of deep and surface approaches, when measured for the whole class, can be used to compare pedagogical characteristics of different courses. Our study measured students’ preferred approaches to learning, as established in the context of a particular course. The discussion activity followed immediately after we gathered the self-reported data, hence there was a rather limited influence of other activities that may have caused the change of the students’ approaches, as the second possible use might have suggested. From this perspective, we can assume that the discovered associations between the quality of the posted messages and the visualization types when controlled for learning approaches arose from the students’ exposure to the visualizations.

The strengths of the associations, especially with the deep cohesion component that is a key component for constructing meaning from the discourse, makes the students’ approaches to learning one of the candidates for measuring individual differences with the goal of selectively offering visualizations to students with certain characteristics. However, before we reach that point, further research is required.

First, we need to reconcile the fact that ideally all the students would engage with the course as deep learners. Students adopt surface approaches because the course design allows it [3]. Hence, it is encouraging to see that there are visualizations, i.e. Top Contributors for surface-motive and Class Average and Quality for surface-strategy, that showed moderate to strong positive association for deep cohesion. It would be interesting to observe if exposure to these visualizations indeed changes students’ approaches to learning, as suggested by Biggs [3] above, or is relatively hard to change, as indicated for example by Gijbels et al. [13].

Second, we need to be aware that we also found negative associations between some approaches to learning and visualizations. These are worrisome for learners with undesirable surface approaches but even more so for learners with the deep-strategy approach when viewing the Top Contributors visualization. Clearly, before we can confidently deploy learning analytics for learners, a better understanding is needed of how the interplay of students’ approaches, context, and the information being presented to students is affecting learning outcomes.

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