Towards a Sentiment Analyzing Discussion-board

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Abstract

In this paper we present the design and construction of a sentiment analyzing discussion board, which was used to support learning and interaction within an existing online social networking (OSN) system. More specifically, this research introduces an innovative extension to learning management software (LMS) that combines real-time sentiment analysis with the goal of fostering student engagement and course community. In this study we perform data mining to extract sentiment on over 6,000 historical discussion board posts. This initial data was analyzed for sentiment and interaction patterns and used for guiding the redesign of an existing asynchronous online discussion board (AOD). The redesign incorporates a sentiment analyzer, which allows users to analyze the sentiment of their individual contributions prior to submission. Preliminary results found that the proposed system produced more favorable outcomes when compared to existing AOD software.

1. Introduction

Academic communities can be classified as niche communities of practice [1]. In these types of communities, individuals work together towards common goals, collaborate on common problems, share best practices, support one another and share in a common identity. Academic communities are founded in the notion that successful learning is collaborative and social, instead of isolated and competitive [2]. More successful academic communities provide for sustained engagement and collaboration among individuals whereby knowledge building becomes an intrinsic function of the community itself [3]. This notion is best represented by engagement theory, which states that students must be meaningfully engaged in learning activities through interaction with others, facilitated and enabled by technology [4].

The technological underpinnings of online or hybrid academic communities are often learning management systems (LMS) such as Moodle or Blackboard. However, as identified in Thoms et al. [5, 6, 7], online social networking (OSN) software has shown to be more effective at replicating face-to-face learning environments, resulting in higher perceived levels of interaction and community and overall levels of course satisfaction. OSN software has also shown success in academic communities by facilitating norms of reciprocity, building trust and providing new opportunities for collective action [8, 9, 10]. Furthermore, OSN software helps students develop shared understandings and mutual support and discussion spaces that can address problems students have with course material [11, 12].

At the heart of online communities are conversations. By their nature, conversations are reciprocal and can take place over numerous media (i.e. blogs, photos or chat). In online learning spaces, many conversations take place within asynchronous online discussions boards (AOD). In fact, the AOD is an integral component of LMS systems; one that often binds individual learning experiences to the course community. AODs are conceptualized by their ability to facilitate cognitive, on-topic, on-task, and sustained discussion among students [13]. AODs also allow students to communicate with their peers using similar language styles [14].

However, a problem with existing AODs is that they can still fall short in fostering the levels of interaction seen in face-to-face settings. Yet students desire greater levels of interaction and collaboration within these tools [15]. In this study, we integrate a sentiment analyzer into an existing AOD to help foster peer-to-peer interactions and enhance levels of community. More specifically, we ask the following exploratory research questions:

R1: Will the proposed system result in a higher number of positive AOD posts?

R2: If R1, will the enhanced system result in a higher number of total AOD interactions?

R3: If R1 and R2, will the enhanced system produce higher levels of course community?

2. Background

In the field of captology, Fogg and Nass [16] state that computing technologies can apply social

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dynamics to convey social presence and to persuade. Within an AOD, social dynamics must come in the form of reciprocity, where individuals participate in back and forth back communication. Reciprocity or, more specifically, norms of reciprocity considers the idea that if an AOD provides a user with a valuable resource, it is a user's responsibility to give back to the AOD in the form of additional interactions.

In [17], Kadushin asserts that interactions (i.e. conversations) lead to sentiments, which can be positive or negative, but positive sentiments lead to further interaction and negative sentiments lead to less interaction. While much research in this space has been done on product or movie reviews, sentiment analysis continues to be studied across other domains (i.e. politics and sports) and media (i.e. blogs, tweets and AOD) [18]. Feidakis et al. [19] express a need for similar research in educational environments, including research in emotion detection systems and their impact on student engagement. In research by Wen et al. [20], conversations from massive open online courses were analyzed to predict course attrition. And in Zarra et al. [21], conversations from StackOverflow were mined to find a larger ratio of negative comments to positive comments. However, to the best of our ability, research has not looked at integrating a sentiment analyzer within an existing AOD, as proposed in this research.

Prior to the redesign of our AOD, we performed an in-depth analysis of existing online conversations using the natural language toolkit (NLTK), which is a broad-coverage natural language toolkit that provides a simple, extensible, uniform framework natural language processing [22]. It can be regarded as a classification technique, either binary (polarity classification into positive/negative) or multi-class categorization (e.g. positive, negative or neutral). While accuracy levels vary across domains, the NLTK provides a valuable open-source resource for connecting to and mining data for sentiment.

A total of 6,083 discussion board posts from a previous AOD were processed through the NLTK and analyzed for sentiment. Detailed in Table 1, 44% of all posts were neutral, 30% were positive and 26% were negative. Within the AOD data, 67% of discussion posts did not receive responses, which could be due to a number of reasons, such as posts being submitted late or simply for the fact that all threads will, inevitably, have a dangling thread. Of these posts, 43% were neutral, 31% were positive and 26% were negative. For discussion posts that received at least one response, 47% were neutral, 28% were positive and 25% were negative. For posts receiving more than four responses (the minimum number of responses per discussion board), 57% were neutral 23% were positive and 21% were negative.

Table 1 – Historical AOD Analysis

Response Count	*Total*	*Pos*	*Neg*	*Neu*
ALL	6083	30%	26%	44%
= 0	4073	31%	26%	43%
> 0	2010	28%	25%	47%
> 1	894	27%	22%	51%
> 2	492	25%	21%	53%
> 3	293	23%	21%	56%
> 4	185	23%	21%	57%

During this analysis, we noticed a trend that as the number of responses per post increased, the percentage of positive responses decreased, as did the percentage of negative posts, while the number of neutral posts increased. Interestingly, this trend is contrary to the notion put forth in Kadushin [17] that asserts as interactions increase, the number of positive interactions will also increase. Additionally, the number of neutral posts were very high, leading us to the idea that innovative software design could guide users to post more positively, thus increasing the levels of activity across the AOD. Simply stated, can innovative system design foster higher levels of positive interactions and, in the process, increase the overall number of interactions?

3. Theoretical Model

The theoretical model adopted in this research is one first proposed [7] and enhanced in [5] and considers three primary constructs for fostering interaction within OSNs. The first construct is constructivism, which prior research has identified as a core ingredient of online community [23, 24, 25]. ***Constructivism*** places the individual at the center and considers the interactions and experiences of the individual as crucial components [26, 27]. These interactions and experiences can be directly influenced by a user's engagement with specific technologies. Thus, innovative design can provide students with a mechanism to connect with others in the virtual and physical space and in a manner they feel most comfortable. In this research we construct a sentiment analyzer, which will allow users to preview the tone of their individual contributions prior to submitting content to the larger community.

Studies have shown that students who are less engaged are more likely to leave the academic community prematurely [28]. Additional studies have found that student engagement can be directly linked to grades and motivation [29]. Thus, getting and keeping individuals engaged in conversations is tantamount to their success. ***Engagement theory*** guides this premise and asserts that students must be meaningfully engaged in learning activities through interaction with others, facilitated and enabled by technology [4]. For this research, dynamic components will facilitate interaction and allow individuals to engage in the content they feel most comfortable engaging with. As proposed in our design, students can view discussion posts from the simple lens of whether or not that post is positive or negative and engage accordingly.

Rounding out this theoretical model is ***social presence theory***, which represents the AOD and, more importantly, the OSN as a whole. Social presence theory looks at the degree to which an individual's perception of the online community, affects his or her participation [30, 31]. When an individual believes that others are interacting and exchanging information, that individual may be more inclined to engage themselves. In this research, we expect that being able to view the overall sentiment of the AOD will allow students to view and perceive that the environment is a largely positive one.

Together, these three theories provide a well-rounded model that considers the overall course community, how individuals decide to interact within the community and how both are influenced and enhanced using technical artifacts.

4. System Design

Prior to the Web 2.0 revolution, Preece [32] stated that OSN developers can control the design of OSN software but it remains difficult to control social interaction across the OSN. While this statement was made to indicate that not all social technologies will yield the desired levels of interaction sought by their design, we believe it is more important to acknowledge that OSN designers have the unique capability to positively impact social interaction.

This concept lies at the core of Design Science Research, where researchers are concerned with the way things ought to be in order to attain goals and devise artifacts to achieve these goals [33]. Today's learning environments are virtual playgrounds for experimenting with new designs that can facilitate learning and foster connection building. Utilizing advances in web technologies, designers are able to construct new information technology (IT) artifacts, or enhance existing ones, to create a more dynamic user-centric learning experience. In this research, our IT artifact is the design and integration of a sentiment analyzer, one aimed at fostering positive interactions and increasing overall levels of engagement.

4.1 Online Social Networking Platform

The importance of an online social networking platform that can adapt to the needs of the instructor as well as the student was critical. Elgg is an online social networking engine that specifically targets learning environments. Elgg provides a range of social features and has an easy-to-use interface. Available through SourceForge.com, Elgg comes bundled with an AOD, blogging, file sharing, the ability to create multiple sub-communities and peer-to-peer (P2P) networking capabilities such as friending and messaging. Additionally, Elgg provides users with the ability to restrict access to data across a number of levels, including individual-level, community-level, logged in user-level and also custom levels of restriction making it a great system for creating multiple course environments. Figure 1 represents the existing threaded AOD contained within the larger OSN system. The threaded discussion is clean and simple and mirrors most traditional threaded discussion boards.

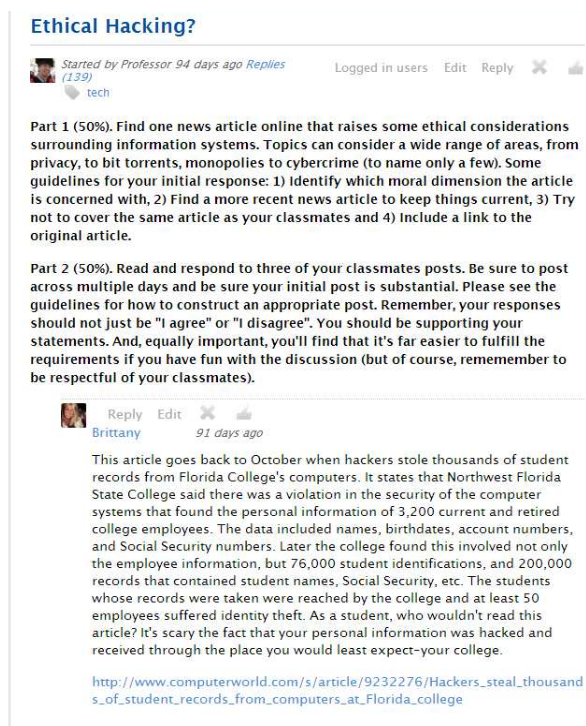

Figure 1 – Existing AOD

4.2 Asynchronous Online Discussion Design

Innovative software design can foster interactions across a website, and new connections can invoke a feeling of freshness for the system, providing users with something new (e.g., blogs, discussions and files) or someone new (e.g., peers and instructors) to interact with. One way to elicit greater levels of interaction is by modifying the AOD, one that promotes and encourages interaction by showcasing positive and negative items. The new AOD design began with the simple rule of thumb, "positive interactions produce more interactions, which in turn are positive."

To elaborate on our design, we break our system down across three layers, 1) data, 2) business and 3) presentation. The presentation layer is what a user will see or interact with. The business logic layer, on the other hand, represents the business rules that are enforced via programming logic (computer instructions) regarding how those rules are applied. The data layer consists of the definitions of database tables and columns and the computer logic that is needed to navigate the database. To conserve space the data layer has been wrapped into the presentation and business layers.

5.2.1 Presentation Layer. The presentation layer proposes three 'views' of the discussion data and looks to incorporate sentiment accordingly.

<u>Response Level</u> (Illustrated in Figure 2) - Individuals can analyze their posts before submitting their responses. Depending on the probability that a post is positive, negative or neutral, a meter is displayed, where green represents positive, red represents negative and gray represents neutral. It should be noted that higher probabilities do not necessarily infer higher levels of sentiment, but rather that there is a higher probability of a post being positive, negative or neutral.

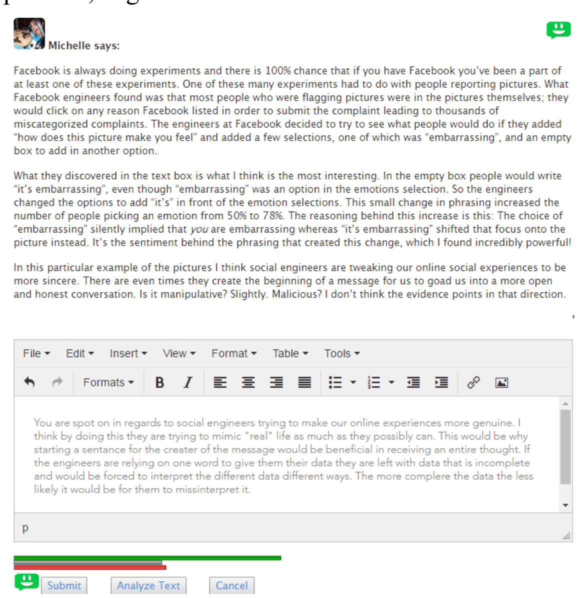

Figure 2 - AOD (Post-Level)

<u>User Level</u> - To the right of the AOD, individuals are also presented with a ranking of sentiment as produced by their peers, from highest positivity to lowest positivity. This feature provided a fun way for students to view whom, among their peers was producing content that was highly positive. To protect the names of individuals, this design feature is not illustrated.

<u>AOD Level</u> (Illustrated in Figure 3) - The AOD, overall, is also provided with a rating, which highlights the overall sentiment of the discussion. This calculation uses aggregate values for all positive, negative and neutral posts per discussion board and divides it by the total posts available for that discussion board.

Figure 3 - AOD (DB-Level)

5.2.2 Business Layer. The business layer considers the underlying algorithms and logic that facilitate the new design. The system leverages the open-source NLTK for processing sentiment. The business layer is illustrated in the System Architecture in Figure 4. Simply put, a discussion reply is sent via the application programming interface (API) to NLTK and the probability of the sentiment being positive, negative or neutral is returned along with the label for that post. At the data layer, the system stores the discussion post in a local database for later processing, as well as the label and probability of the post being positive, negative or neutral.

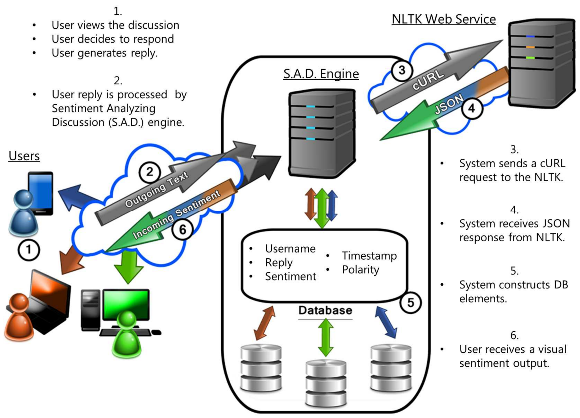

Figure 4 – System Architecture

5. Methodology

Our study can be categorized as a between-group, quasi-experimental design. Similar to the characteristics of a field study [34, 35], we measure the effects of our proposed design on a specific population within an existing organization. While the organization, an undergraduate school, is not a "naturally" occurring setting, it is pre-existing and baselines exist for which to compare results.

To measure the impact of the proposed system, data across a control group (Group 1) and treatment group (Group 2) were collected and analyzed. To the best of our ability, content for each group was delivered in exactly the same manner. For each group, the number of required posts per user was four (one initial post and three response posts). The only significant difference was that Group 1 utilized a more traditional AOD, while Group 2 received the redesigned AOD.

6. Results

In total, 1,273 online conversations were analyzed using the NLTK API. In addition to a content analysis, a social network analysis (SNA) was performed using NodeXL. Perceived levels of online community, perceived levels of interaction and perceived levels of overall learning were also captured.

6.1 Content Analysis

6.1.1 Site Usage. Group 1 consisted of 19 individuals. The total number of pages visited was 18,621 pages, or 980 pages per person. The total number of discussion posts created and analyzed was 563 or 30 per individual. Group 2 consisted of 22 individuals. The total number of pages visited was 22,937 pages, or 1,043 pages per person. The total number of discussion posts created and analyzed was 710 or 32 per individual.

6.1.2 Sentiment Analysis. Table 2 and Table 3 detail the number of responses for posts based on the sentiment of those posts. Overall, each group posted an equal amount of positive posts, although Group 1, on average, posted more negative posts at each level. Additionally, trends show that while the number of positive posts decreased as the number of response posts increased for Group 2, this trend was reversed for Group 1.

Table 2- Group 1 Sentiment Analysis

Response Count	*Total*	*Pos*	*Neg*	*Neu*
ALL	563	50%	31%	20%
= 0	397	50%	32%	18%
> 0	166	49%	29%	22%
> 1	80	53%	31%	16%
> 2	55	51%	27%	22%
> 3	41	51%	34%	15%
> 4	27	48%	41%	11%

Table 3 - Group 2 Sentiment Analysis

Response Count	*Total*	*Pos*	*Neg*	*Neu*
ALL	710	50%	25%	25%
= 0	489	51%	26%	24%
> 0	221	49%	23%	28%
> 1	102	41%	27%	31%
> 2	63	51%	22%	27%
> 3	42	45%	21%	33%
> 4	30	40%	30%	30%

6.2 Social Network Analysis

6.2.1 SNA Background. An SNA can be used to identify interactions that take place within an associated network. Specifically, SNAs help to provide a visualized analysis of a social structure and allow for a better understanding of all individuals in the process of learning and interaction across online environments [36]. The ability to view social graph structure and community evolution can be a crucial measure of a software design and can serve as an early indicator of its success [37].

6.2.2 SNA Design. To measure the AOD design, SNA graphs were constructed using the 2014 NodeXL Template for Microsoft Excel. NodeXL is a free and open source extension, which provides a range of basic network analysis and visualization features [38]. Utilizing the Fruchterman-Reingold algorithm to generate a force-directed layout, we are able to position users (aka, nodes) in our graph so that all edges are of more or less equal length and there are as few crossing edges as possible. Additionally, each arrow represents a weighted interaction, where larger arrows indicate a greater number of interactions between individuals. Furthermore, bi-directional arrows occur when there is interactivity between students, measured in-degree and out-degree values. A higher average value for in-degree and out-degree indicates that those students more frequently interacted with one another.

6.2.3 SNA Sociograms. SNA graphs were generated for Group 1 and Group 2. Illustrated in Figure 5 and Figure 6, individuals are depicted by their placement within the graph as well as by their aggregate polarity of sentiment. Positive or negative ratings were assigned by taking the absolute value of the difference in positive and negative posts. For example, larger green triangular nodes represent individuals that posted a greater number of positive posts versus negative posts, while smaller red circular nodes depict individuals who posted slightly more negative posts than positive posts. Larger lines represent greater levels of interactions between nodes. Neutral nodes, depicted by blue squares, are assigned to users where the aggregate number of neutral posts exceeded the total number of positive posts and negative posts combined. The total number of posts per user is indicated directly below each node.

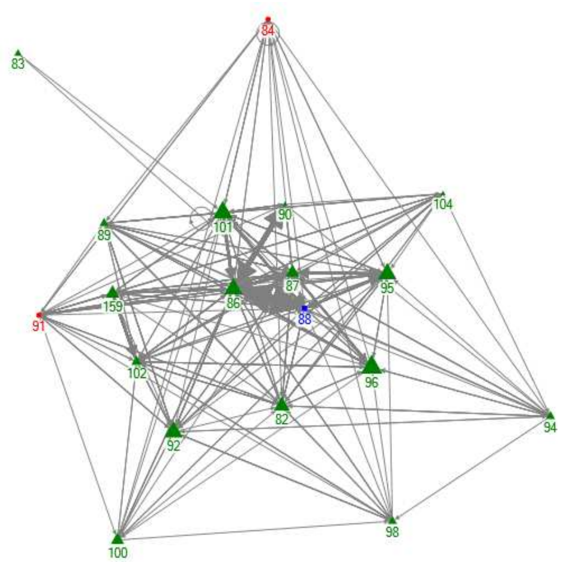

Figure 5 - SNA Group 1

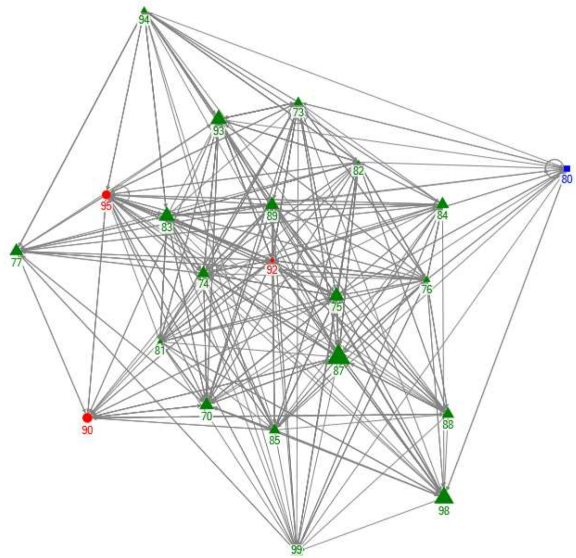

Figure 6 - SNA Group 2

6.2.4 SNA Metrics. Identified in Figures 5 and 6, Group 2 yielded higher in-degree / out-degree at 12.8 compared to Group 1's 9.7. This indicates that the frequency of interactions was higher across Group 2 users. In other words, on average, users responded to more of their peers. Additionally, the total number of unique edges was higher across Group 2 (149 unique edges) compared to Group 1 (97 unique edges). Lastly, density, which is calculated by taking the total number of existing connections and dividing it by the total number of possible connections, was higher for Group 2, at 6.0, than for Group 1, at 5.3.

6.3 System Feedback

System feedback from individuals was ascertained and offered valuable insights on the perceived ease of use and perceived usefulness of both systems and provided for a modest baseline for comparison. For all instruments, a five-point numeric scale was used. In total, feedback from 40 individuals was obtained.

6.3.1 OSN Design. The first set of questions focused on users' general perceptions of the sentiment analyzer. Instruments were measured for internal reliability across this construct, resulting in a Cronbach's alpha score of .66. While this score was slightly below the generally accepted value of .70, it is not too far below and thus provides interesting insights into student's general perceptions. Detailed in Table 4 are responses to those items.

Discussed in more detail in the discussion section, overall, users indicated that the new design had an impact on their behavior with 59% agreeing or strongly agreeing that the system affected their interaction, 63% agreeing or strongly agreeing that the design influenced the tone of their posts and 68% indicating that it was helpful to know the tone of their posts. Additionally, 63% of users agreed or strongly agreed that viewing sentiment facilitated engagement and 59% of users agreed or strongly agreed that the system made them want to post more.

Table 4 – System Design

SA=Strongly Agree, A= Agree, N=Neither Agree nor Disagree, D=Disagree, SD= Strongly Disagree

Item	SA	A	N	D	SD	AVG	STDV
The system affected my interaction in the discussion.	27%	32%	18%	23%	-	**3.64**	**1.14**
I made an effort post positively to the discussion.	27%	59%	5%	9%	-	**4.05**	**0.84**
It was helpful to know the tone of my posts.	27%	41%	18%	9%	5%	**3.77**	**1.11**
Discussion tone influenced my response tone.	27%	36%	18%	9%	9%	**3.64**	**1.26**
Positive posts were more valuable.	23%	32%	14%	14%	18%	**3.27**	**1.45**
Positive posts were more interesting.	18%	36%	23%	9%	14%	**3.36**	**1.29**
Seeing sentiment facilitated engagement.	18%	45%	14%	9%	14%	**3.45**	**1.3**
The system prevented me from expressing my true feelings.	18%	45%	5%	18%	14%	**3.36**	**1.36**
Positive discussion boards increased course community.	23%	50%	9%	9%	9%	**3.68**	**1.21**
Positive discussions increased interaction with my classmates.	18%	55%	9%	9%	9%	**3.64**	**1.18**
The system made me want to post more.	18%	41%	23%	9%	9%	**3.50**	**1.19**

6.3.2 Community and Interaction. A second set of questions focused on students' perceptions of interaction and community. Pre-validated instruments were measured for internal consistency across this construct, resulting in Cronbach's alpha scores of .86 for the pretest instrument and .84 for the posttest instrument, suggesting that these instruments had adequate levels of internal consistency. Detailed in Table 5 and Table 6 are responses to those items.

Focusing specifically on levels of interaction and community and discussed in detail in the discussion section, there was an overall shift in levels of perception from pretest to posttest across both constructs for both groups. However, for Group 1 this shift was downward, while Group 2 experienced an upward shift. For perceived levels of interaction, Group1 saw a decrease in overall levels of agreement (90% to 82%) versus Group 2 (78% to 96%). For perceived levels of community, Group 1 saw a decrease in overall levels of agreement (90% to 70%) versus Group 2 (74% to 91%).

Table 5 – Interaction and Community (Group 1)

SA=Strongly Agree, A= Agree, N=Neither Agree nor Disagree, D=Disagree, SD= Strongly Disagree

Item	SA	A	N	D	SD	AVG	STDV
(Pre) High levels of interaction will be important.	35%	55%	10%	-	-	**4.25**	**0.64**
(Post) High levels of interaction were important.	35%	47%	12%	6%	-	**4.12**	**0.59**
(Pre) Learning through collaboration will be important.	20%	55%	25%	-	-	**3.95**	**0.69**
(Post) Learning through collaboration was important.	22%	35%	35%	4%	4%	**3.65**	**0.94**
(Pre) Exchanging feedback with other members will be important.	20%	75%	5%	-	-	**4.15**	**0.49**
(Post) Exchanging feedback with other members was important.	47%	41%	6%	-	6%	**4.24**	**0.51**
(Pre) A sense of community will be important.	35%	55%	10%	-	-	**4.25**	**0.64**
(Post) A sense of community was important.	29%	41%	18%	6%	6%	**3.82**	**0.79**

Table 6 – Interaction and Community (Group 2)

Item	SA	A	N	D	SD	AVG	STDV
SA=Strongly Agree, A= Agree, N=Neither Agree nor Disagree, D=Disagree, SD= Strongly Disagree							
(Pre) High levels of interaction will be important.	30%	48%	17%	4%	-	**4.04**	**0.82**
(Post) High levels of interaction were important.	64%	32%	5%	-	-	**4.59**	**0.59**
(Pre) Learning through collaboration will be important.	22%	43%	26%	9%	-	**3.78**	**0.9**
(Post) Learning through collaboration was important.	41%	41%	9%	9%	-	**4.14**	**0.94**
(Pre) Exchanging feedback with other members will be important.	30%	35%	35%	-	-	**3.96**	**0.82**
(Post) Exchanging feedback with other members was important.	55%	45%	-	-	-	**4.55**	**0.51**
(Pre) A sense of community will be important.	35%	39%	26%	-	-	**4.09**	**0.79**
(Post) A sense of community was important.	50%	41%	5%	5%	-	**4.36**	**0.79**

7. Discussion and Implications

Exploratory research questions centered on whether the new design would foster more positive posts and if these positive posts would yield greater levels of interaction.

7.1 Sentiment

This research began with the simple premise that interactions generate sentiments, which can be positive or negative, but positive sentiments lead to further interaction and negative sentiments lead to less interaction. Feedback from system users identified that the system positively influenced how users viewed posts across the AOD and allowed users to reflect on the tone of their individual posts compared with responses from the group. These findings extend the limitations of prior AOD research as identified in [19] and demonstrates an unobtrusive and non-invasive design for evaluating students' affective state.

In R1, we asked if the new AOD would increase the total number of positive posts. Overall, the total number of positive posts was the same across both groups, although the total number of negative posts was slightly lower (Table 2 and Table 3). Further comparing this data, we discovered that the control group followed theoretical underpinnings and as the number of response posts increased, the overall number of positive posts increased as well. However, so did the number of negative posts, which runs contradictory to theoretical underpinnings. Within the treated group, we discovered a different trend and as the number of response posts increased, the number of positive and negative posts decreased, resulting in a higher percentage of neutral posts. In one sense, this uptick in neutral responses can be seen as a positive trend, considering that discussion topics, oftentimes, covered polarizing subject matter such as net-neutrality and cyber-ethics. Thus, having a system that affords students the ability to gauge the tone of their response may have helped keep conversations more topic-focused and academic in nature, although a more detailed content analysis would be required to fully support these claims.

7.2 Community and Interaction

If we acknowledge that R1 was successful, if not in resulting in more positive posts, but in reducing the number of negative posts, we can turn our attention to R2, which asked if the AOD could produce more interactions. Overall, the treated group posted more, 32 replies per user versus 30 replies per user in the control group. Additionally, system feedback from individuals identified that the system positively influenced interaction across the AOD.

R3 asked how, given R1 and R2, the new design build a greater sense of community. To better understand how the new design facilitated these constructs, we return to the SNA, and how the density of the community differed across both networks. Density is often measured to be the heart of a social network and is used to determine the strength of the ties between all individuals in that network. Alone, this number provides little meaning, but when compared against a benchmark, the number can provide great insights into the strength of a network. Consequently, when we compared the SNA metrics of Group 1 and Group 2, we discovered that students participating in Group 2 maintained a more dense network than Group 1. This was surprising for the simple reason that as a network becomes larger (18% in the case of Group 2), density generally decreases (think Facebook, or the physical Universe, as examples). In an educational setting, this often holds true and as a classroom population grows, meaning more students enroll and participate, it becomes less likely that all students will be able to connect to more students. Although further analysis is required, we attribute a portion of this success to the enhanced AOD design, which presented users with added metadata based on the sentiment of their peers' responses. This metadata allowed users to quickly navigate the discussion and choose posts they felt more comfortable responding to. This is an important fact since, as found in Qiu and McDougall [39], students in an online discussion general skip reading 39% of posts, tending to choose topics and select authors they like to read or respond to.

Finally, and at a higher level, the new design presented users with, more often than not, a positive picture of the overall discussion. While the control group maintained an equal number of overall positive posts, there was no way for those users to see how positive the AOD environment was, which could have contributed to the higher levels of interaction and community our treated group perceived.

7.3 System Design and Expansion

This system represents version 1.0 of integrating a sentiment analyzer into an existing AOD and there are greater goals for further expansion of the system. In total, the sentiment analyzer was used 443 times or roughly 62% of the time. A future design goal may be to require individuals to review the sentiment of a post before submitting. Additionally, we acknowledge that using a color scheme to represent sentiment can impact the, roughly, 4.5% of the population that experiences color-vision deficiency. Therefore, a more novel approach will look to adopt features that could support this population as well, including better use of emoticons or emojis. Furthermore, the current version of NLTK was trained against movie review data sets [40] and would need to be retrained for more accurate results using AOD data specific to this domain. Finally, the implementation of a sentiment analyzer across other types of OSN data, such as blogs, tweets and instant messaging could also yield higher levels of interaction and community.

8. Limitations

As exploratory research into improving the design of an existing AOD, the authors acknowledge some of the limitations in this research. Firstly, our population size was small (19 users for the control group and 22 users for the treated group), which prevented results from achieving statistical significance. Secondly, the enhanced AOD design was partly contingent on how effective the NLTK was at identifying sentiment. As experimental software, the NLTK did not always return the most accurate results. As this research expands, we will explore different approaches to data mining user sentiment that more accurately considers academic discussion board data.

9. Conclusion

In this research we perform a historical analysis of sentiment across an existing OSN. This analysis helped to guide the redesign of the OSN's AOD. The new design, which consisted of a sentiment analyzer, was pilot tested with largely positive results. Overall, the new system produced a higher average number of responses per user. Additionally, users responded with higher levels of perceived interaction and community and SNA results identified a more dense online community compared against control group data. The results provide a valuable starting point for system expansion and the possibility of integrating a real-time sentiment analyzer into other media components such as blogging and twitter.

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