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Twittermania: Understanding How Social Media Technologies Impact Engagement and Academic Performance of a New Generation of Learners

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Abstract:

Twitter, a popular micro-blogging service, is increasingly evolving from being a mere chatting platform to a tool that is instrumental in affecting a desired learning and social change among individuals and organizations. Although using Twitter for learning while socializing represents a significant departure from its intended initial function, information systems (IS) researchers should further explore the impact and implications of social media technologies such as Twitter in the educational context. We draws on engagement theory and social impact theory to assess how social media technologies tools can support learning and improve students' academic outcomes. We present an experiment in which we compared Twitter and a traditional discussion board to academically engage students over a 14-week period. The results show that actively using both Twitter and traditional discussion boards for engagement is related to student performance in the course. Social network analysis suggests that, by using Twitter, the students possibly created shared mental models that led them to engage with the class more, and therefore, better their performance.

Keywords: Twitter, Engagement Theory, Performance, Technology-mediated Learning, Social Impact Theory.

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1 Introduction

Social media is increasingly growing in acceptance and usage across several domains. The most common social media technologies (SMTs) that have reached significant penetration include Twitter, Facebook, YouTube, and LinkedIn, but many more are emerging. One can access SMTs via any device connected to the Internet such as a smartphone, computer, or notebook. An advantage of SMTs such as Twitter is the immediacy with which one can share information with other users, which makes it appealing for generating and maintaining engagement. In addition to providing information to users at a fast pace, access to these technologies is ubiquitous, which gives users the ability to instantaneously respond to information.

The interactive platform that social media affords makes them viable learning tools, but instructors continue to debate their role in the classroom. Some instructors consider the use of any form of social media in the classroom to be a distraction and ban such use during class time (Galagan, 2010). They are convinced that the adoption of social media technologies is responsible for ill social behavioral problems among users and, in particular, students (Galagan, 2010). While these instructors view social media technologies as a form of "behavioral menace to society", others (Kane & Fichman, 2009) view them as a viable tool for engaging students (Grosseck & Holotescu, 2008). In this paper, we focus on how to leverage Twitter to engage students with their course materials "in" and "out" of the classroom. The proximity of a vast amount of information resources that Twitter avails its users makes it a viable platform to share information while providing experiential learning activities (Roth & McCully, 2010).

Students in the information age are becoming more technologically savvy, which is leading educators to rethink how to engage these learners with the course materials. SMTs can potentially provide educators with the opportunity to foster engagement and interaction in their classrooms. Some studies suggest that using social media technologies such Twitter is invaluable to engage learners via a medium they are familiar with and find interesting (Grosseck & Holotescu, 2008). Twitter forces its users—learners and educators—to interact via "tweets" on their smartphones, laptops, notebooks, or any device with Internet access using only 140 characters. Research has associated the act of condensing information into concise units with the internalization of the concept learned (Wyer, 2004)—the act that transforms information into knowledge. Since internationalization is a key outcome of actual knowledge absorption, SMTs can facilitate knowledge sharing. Hence, Twitter's 140-character limit per tweet may offer an innovative model that encourages students to generate topical and shared mental models for subsequent synthesis and evaluation (Schroeder, Minocha, & Schneider, 2010). Moreover, the spontaneous interaction patterns on microblogging services –such as Twitter provide a shared space for participants to collaboratively validate their mental model representations of the discussion topic (Holland, Holyoak, Nisbett, & Thagard, 1986). In response to calls for research in the IS discipline on appropriating SMTs tools in teaching (Kane & Fichman, 2009), we draw from engagement theory (Kearsley & Shneiderman, 1998) and social impact theory (Latane, 1981) to investigate how educators and students can leverage Twitter as an innovative tool to support engagement and learning.

2 Theoretical Background

2.1 Student Engagement

Research has viewed the concept of student engagement from several perspectives. Aston (1984) defines student engagement as the amount of physical and psychological energy that a student devotes to the academic experience in the course of attending an academic institution. More specifically, Chickering and Gamson (1989) offer seven practices that demonstrate student engagement during the course of an undergraduate degree: 1) student-faculty contact, 2) active learning, 3) respecting diversity, 4) communicating high expectations, 5) emphasizing time on task, 6) cooperation among students, and 7) prompt feedback. Furthermore, Kuh (2009) presents a modified conceptualization of student engagement, which suggests the need to empirically link college outcomes to educational (course-related) activities and extra-curricular (non-course-related) activities (Pascarella & Terenzini, 2005). Researchers have demonstrated that student engagement, from both course-related and extra-curricular engagement perspectives, is vital in the learning process. Student engagement is necessary for retaining information (Barkley, Cross, & Major, 2004; Shulman, 2002) and critical to motivating student learning (Wishart & Blease, 1999).

As such one can view engagement from two perspectives that both influence students' overall academic performance. On the one hand, we refer to activities that challenge and extend students' intellectual capacity to engage with academic activities since such activities avail students the opportunity to synthesize concepts taught in class and, thus, gives them the ability to critically analyze observations beyond the classroom. One can consider interaction between students on knowledge-synthesizing activities as fully engaging when students can collaborate on those activities with colleagues, faculty, and other professionals in their area of expertise. This perspective corresponds to the constructivist teaching approach that emphasizes social and collective learning among students (Schroeder et al., 2010). On the other hand, we refer to activities that contribute to a student's educational experience beyond the synthesis of concepts taught in class and that focus more on the student's social interaction as non-academic engagement. Examples of such activities could include various sports, membership in associations, and other extra-curricular activities. This study focuses on the academic perspective of student engagement and explores how Twitter can support the learning process both inside and outside the classroom in terms of facilitating course-related discussions and interactions with classmates.

2.2 Social Media Technologies (SMTs) and Engagement

To further explore the potential of technology in stimulating student learning, we review engagement theory in the context of its role in facilitating interactions and knowledge exchanges. Engagement theory is a teaching and learning framework predicated on the notion that engaging with course materials and course-related activities are essential for learning that is effective for students (Kearsley & Shneiderman, 1998). The theory posits that accomplishing engagement involves collaboration, task assignment, and a focus on non-academic topics. The theory suggests that these three methods result in creative, meaningful, and authentic learning outcomes (Kearsley & Shneiderman, 1998). Social media tools (such as Twitter) support collaborative efforts in which users can deliberate and discuss concepts learned in class and apply, connect, and research other links outside the class (e.g., a marketing campaign to promote a small business in the community as a project in a marketing course). Students can use social media such as Facebook, Twitter, Linkedin, and so on to execute the project. Drawing from engagement theory (Kearsley & Shneiderman, 1998) and perspectives that we describe in Section 1, we define student academic engagement for the purpose of this paper as the process that allows students to actively and collectively review and process course content while motivating them to learn in a conducive environment (using technology tools and artifacts with which they are familiar).

Researchers have purported that one can use technology to engage students in the learning process (Alavi, Marakas, & Yoo, 2002; Baker, Gearhart, & Herman, 1994; Chen, Lambert, & Guidry, 2010; Dwyer, Ringstaff, & Sandholtz, 1990; Means & Olson, 1994). More importantly, one can use social media technologies to engage students since they are more familiar with such technologies compared to traditional learning management systems. Researchers have shown that using social technologies in creative ways can improve learning (Wishart & Blease, 1999). In sum, social technologies avail educators the opportunity to engage students while improving their learning by using technology-supported, pedagogically sound instructional strategies (Bryant & Hunton, 2000). Note that theories that researchers have used to espouse engagement in a traditional classroom setting may not sufficiently explain interactions and outcomes in a technology-mediated learning environment. With this study, we contribute to the understanding required to theorize about relationships between social media technologies, student engagement, and learning. Given the complexity of learning and the many elements that contribute to classroom performance, we do not attempt to establish causality between social technology use and learning. Rather, we provide empirical evidence of a relationship between social technology and learning support, which ceteris paribus one may then use theorize about the nature of the relationship.

2.3 Twitter in the Classroom

Many studies have mentioned the potential of using Twitter in the classroom and in a learning context. Young (2010) experimented with using Twitter in the classroom to post questions on course-related content during routine class sessions. The study concluded that using Twitter alters the classroom power dynamics in favor of students, which some faculty members may not like. Grosseck and Holotescu (2008) prescribe a list of features supported by Twitter that, if implemented correctly, may enable it to become an effective learning platform for students. Specifically, Twitter can facilitate collaboration, knowledge sharing, and composition. On the other hand, the authors indicate that 1) the 140-character limit could lead to bad grammar, 2) it can be time consuming to use Twitter, and 3) it can become addictive to the point of being a distraction.

In a semester-long study to explore how students react to the use of Twitter to create social presence while learning, Dunlap and Lowenthal (2009) report that engaging students in an online course with Twitter was more beneficial compared to using traditional learning management systems. Similarly, Borau, Ullrich, Feng, and Shen (2009) analyze the usefulness of Twitter in second language learning. They argue that, in the learning process, learners need to actively produce language and be given a chance to practice the language by actively engaging in conversations with others. Using Twitter trained communicative and cultural competence among the observed students.

While most studies have demonstrated the potential of using Twitter as a tool for learning in classrooms, a Welch and Bonnan-White (2012) report non-statistically significant differences in student engagement when using Twitter in a large-lecture university class, which could have resulted from participants' demographics, their efficacy in using Twitter, or other confounding factors they mention in their limitations section. Further, they approach the authors took to asses assess engagement could have contributed to their results. Hence, we need to identify the learning objectives associated with the chosen social technology capabilities to properly use it for engagement and control for confounding factors that may affect classroom learning.

2.4 Social Impact Theory

Studies show that computer-mediated communication among college students better fulfills information-seeking, convenience, connectivity, and content-processing motivations compared to non-computer mediated communication (DeAndrea, Ellison, LaRose, Steinfield, & Fiore, 2012; Guo, Tan, & Cheung, 2010). Students may experience the positive outcomes of such computer-mediated interactions as they communicate with one another over the course of a semester. Therefore, social exchanges may affect their behavior, which we refer to as social impact. Social impact describes behavioral changes that people cause (intentionally or unintentionally) in other people as a result of the way the changed people perceive themselves in relationship to the influencers, other people, and society in general (Latane, 1981). The potential influencers in the context of our study are other students in the same institution. We draw on social impact theory (SIT) to better understand social impact that results from using computer-mediated communication tools. SIT posits that social impact results from the existence of social forces in a social structure. A corollary of SIT that governs social impact is also known as the psychosocial law. According to psychosocial law, a critical point of social impact is what occurs when the source of stimulus (i.e., number) increases from nothing to the next unit of measurement. The law also posits that, as the number of sources of stimulus increases, the social effect response begins to reduce until it is eventually marginal. In essence, the higher the number of discussants, the less impact each discussant feels. According to the first rule (Latane, 1981), three multiplicative factors—strength, immediacy, and number—constitute the social forces that contribute to increasing an individual's likelihood to respond to social influence. "Strength" refers to the source of the impact, "immediacy" refers to the recency of the event (which, in this study, relates to the timeliness and relevance of the discussion with respect to the weekly discussion topic), and "number" refers to the number of other discussants. Since we focus on academic discussion, social exchanges will lead to learning, which repeated discussions should reinforce. Overall, based on SIT (Latane, 1981), we argue that using Twitter for actively discussing course content creates a social structure that leads to higher social impact but that such impact may decrease if the number of participants increases. We argue that social structure will influence participation, and students with higher participation intensity will perform better than those with lower participation intensity.

2.5 Objectives and Research Questions

We compare a control group that used a specific SMT (Twitter) with a control group that used Moodle (a learning management system) to observe how using each technology impacts students' engagement and academic performance. Twitter provides a flexible process of sharing, communicating, and receiving updates—attributes that engagement theories posit to support students' academic and social engagement. In addition, as users communicate more about the course material, they internalize course information and can use it in other contexts. Consequently, they enrich their understanding of the course material and may perform better than students who collaborate on platforms with less enjoyment or satisfaction.

Although researchers have proposed some models to help appropriate social media into pedagogy (e.g., Kearsley & Shneiderman, 1998; Roth & McCully, 2010; Schroeder et al., 2010), the majority of them are prescriptive at best. We found only two studies that empirically investigated relationships between the use of Twitter and students' learning performance with subjective self-reported data (Junco, Heiberger, & Loken, 2011; Welch & Bonnan-White, 2012). Rather than quantifying engagement with a subjective survey instrument, we objectively measured engagement by tracking the intensity of students' participation in course discussions with other students throughout a semester. This approach rests on the claim from engagement theory that espouses engagement as the actual interaction among learners rather than self-reported perceptions of their interactions with one another. Furthermore, as a result of the dearth of empirical research on the impact of social media technologies (such as Twitter) on learning and/or academic performance (final grade), we need to understand the mechanics of how people interact with Twitter for educational purposes.

Drawing on SIT, we focus on how the network structure of students who interact on Twitter can impact their academic performance. Social network analysis (SNA) presents three classic network structural mechanisms (or centrality measures) that one can use to analyze such a network: degree centrality, betweeness centrality, and closeness centrality (Freeman, Roeder, & Mulholland, 1979; Newman, 2005). Betweeness centrality measures the extent to which a node acts as a bridge along the shortest path between two other nodes in the network. Closeness centrality measures how far a person is from all others in the network. Degree centrality defines the number of links incident on a node, which also measures how well connected each individual is in the network. In a directed network, where links between network nodes have directions, degree centrality accounts for the source of traffic "in" and "out" of a node. In other words, a node becomes well connected either when it connects to many other network members (outdegree) or when other nodes in the network connect with that node (indegree). These centrality measures align well with the dimensions of social impact theory that we use in this study. For instance, betweeness centrality operationalizes the strength of the social impact of other students with whom a student is connected. Betweeness considers the "status" of the other nodes that warrants connecting to in order to bridge the gap between the shortest paths in the network. Closeness centrality operationalizes immediacy in the network since it measures the shortest path between a node and other nodes in the network. Closeness guarantees the timeliness of getting information from one node to the next. Degree centrality operationalizes the number of connections with other students in the network. Since number focuses on the combination of nodes exercising influence that is socially desirable on a given node (the target student), SNA provides indegree and outdegree centrality measures to estimate a node's potential to be a source of influence or to be influenced by external sources, respectively.

To summarize, using university students in the United States, this study extends previous research by using a quasi-experimental design to investigate the relationship between students' Twitter use and academic performance as a function of their engagement in course work while keeping other possible covariates constant. Drawing from existing findings on the relationship between engagement and student success, we measured learning performance as the final grade received in the course (Junco et al., 2011) and student engagement through the intensity of students' participation in online interactions. The following broad research questions guided the exploration we describe in this paper.

RQ1: Does the collaboration platform (Twitter vs. Discussion Board in Moodle) used for learning influence students' academic engagement?

RQ2: Is there a relationship between Twitter use in academic discussions and student performance?

RQ3: Does social impact theory explain the observed network structure in Twitter's discussions?

3 Methodology

To help others replicate our study, we describe the methodology we employed to gather, prepare, and analyze data in this section. We present how we conducted the procedure (Appendix A provides a sample of directions we gave to the students) and information on the sample population that participated in this study. Furthermore, we describe how we collected data and define the variables we used to analyze it.

3.1 Procedure

We announced our study to four sections of an introductory management of information systems course during the first week of the first semester in 2012. We randomly assigned students to one of two groups (Shadish, Cook, & Campbell, 2002): 1) the control group that used the discussion forum on Moodle (a learning management system) to discuss weekly assignments and 2) the treatment group that used

Twitter to discuss the assignments. Moodle is an open-source learning management platform that educators, administrators, and learners use to create personalized learning environments (visit https://moodle.org/ for more information). This platform allows an instructor to load course materials online and control access to registered students. The feature most relevant to this study is the discussion forum, which allows registered users to create threaded conversations. For our study, we created twelve discussion threads to guide weekly discussions throughout the study period.

We gave participants in the treatment group instructions on how to register on Twitter if they were not registered already and a tutorial on how to post tweets, retweet, and post a reply to a tweet (see Appendix A for the instructions). Students in the treatment group had to post at least one tweet and at least two replies to other students' tweets each week. In the tweets, they had to discuss how concepts taught in class relate to their everyday activities and the tweets had to contain examples of the concepts. Similarly, we provided participants in the control group instructions about how to use discussion forums to post and edit messages. As with participants in the treatment condition, they had to post at least one message and respond to at least two messages weekly. Over fourteen[1] weeks, participants could accumulate as many as 6 points if they posted at least one message and two replies weekly. We used the extent to which participants posted messages as a measure of their participation intensity—a proxy for measuring engagement.

Discussions could include responses to questions in the form of suggestions or solutions based on knowledge acquired from the course. In the Twitter condition, communication rules included using hashtags (#) to identify the student, the course, and the week of participation. As Table 1 shows, the first record shows a tweet in the fourteenth week (wk14) from one student (std1) in section 1 (sec1) of the class. Note that tweets simply contain the sender's name (std1), the section of the class (sec1), the week of participation (wk14), and the text. The second record in the table shows a response from one student (std2) to another (std3) in section 1 (sec1) of the class in the tenth week (wk10). To distinguish tweets from replies, Twitter automatically precedes the username of the student being responded to with a "@" sign as in the second example in Table 1.

Table 1. Sample Tweet and Response from the Dataset

#std1 #sec1 #wk14 DHS is monitoring social media for breaking news - Washington Times: wtim.es/JNABRU via@washtimes
@std3 #std2 #sec1 #wk10 is social media replacing traditional media? Do organizations use social media to search for useful information?

3.2 Participants

We used four sections of a three-credit management of information systems course[2] that the information systems and management departments at the university in question jointly offered as a recruitment location for this study. We chose this course for three reasons:

1) To control for instruction delivery bias since the same instructor taught all the sections
2) To provide a good sample of the student population since all majors take the course, and
3) Because each section corresponded to the classification of the students (i.e., sections 1 and 2 comprised fourth-year and third-years tudents and sections 3 and 4 comprised second-year and first-year students).

Students did not have to participate, but we incentivized their doing so with draws to win gift cards from Barnes & Noble and Amazon throughout the semester. We also awarded extra credit points based on their participation as we describe earlier.

In total, 212 students from the sections of the course registered to take part in the study. We distributed them equally between the two experimental conditions. However, only 164 students completed the study. To verify whether the unequal sample size and mortality constituted a selection bias, we analyzed the

[1] We discussed new content for only twelve weeks. The other two weeks in between the semester resulted from breaks.
[2] The course was structured to encourage students to seek out the operationalization of concepts introduced in class in their everyday lives. They needed to hand in four essays throughout the semester to discuss information technology implementations, identify issues with the implementations, offer suggestions on how to improve them, and present a proposal to implement an information system to support a business process in a chosen industry.

dropouts' age, gender, course grade, and years spent in college. We found no significant difference between the dropouts and the continued participants in the study.

The first author's university's internal review board (IRB) approved the study. As the IRB required, we assigned an alternate task to non-participants to earn extra credits. Although we randomly and equally assigned participants to both experimental conditions, 21 participants exercised their right to voluntarily switch from the control group to the treatment group. Seventy-eight percent of the participants were males. The age of the participants ranged from 18 to 29 years old.

3.3 Data Collection

The dataset comprised the conversational data from Twitter and Moodle and the performance of the participants that the instructor submitted in all the sections of the course at the end of the semester. We collected the conversational data from the interaction between participants across four courses via Twitter API over a 14-week period. The API allows one to collect data such as the date and time each tweet was posted, the content of each tweet, and the username for both the sender and receiver.

Drawing from prior research, we measured learning performance as the final grade received in the course (Junco et al., 2011). To avoid confirmation bias in the research design, the instructor (the first author) created a rubric for grading the course, and two independent graders—colleagues of the researcher and experts in the research area—graded 50 percent of the students' finals from each course section. We employed two other graders (PhD students) to grade all the finals from all the course sections. Since we used more than two raters, we used Cohen's kappa (Cohen, 1960) to compute inter-rater reliability as prior research recommends. The inter-rater reliability of the final grade from both set of graders was 0.98.

3.4 Variables and Data Analysis Techniques

We used participation intensity as a proxy for engagement. Students could earn a total of 6 points[3] in extra credit, which indicates that the participant posted at least the minimum required number of tweets and replies throughout the study period. We categorized participation intensity based on the earned extra credit points. We classified students with at least 5 extra credit points as participants that exceeded participation expectation, those with extra credit points between 3 and 5 as those that met the participation expectation, and those with less than 3 extra credit points as below expectation. The Kurtosis assessment of the dependent variable (final grade) indicated that the 95% confidence interval for the kurtosis score contained zero, which indicates that the statistic was not significantly different from a distribution of zero. Therefore, the dependent variable was normal.

We used SPSS (ver. 20) and UCINET to conduct the analyses. Although the data is normal, given the unequal sample size due to dropouts from the experiment, the data failed to confirm to Levene's test of homogeneity of variance. However, prior work indicates that one can conduct a two-way analysis of variance (ANOVA) when one assumes the variances of the two samples to be equal or unequal using the Welch option in SPSS (NIST, 2003). In order to answer the research questions, we conducted a two-way ANOVA to examine the relationship between participants' performance and the platform they used for discussion. Specifically, we used a fixed-effects model ANOVA to assess how using Twitter for discussion relates to students' performance as compared to using the discussion forum in the control group in Moodle. The categories we used were: 1) the discussion platform—Moodle (control group) or Twitter (treatment group), 2) the class section—sections 1 to 4, and 3) the participation intensity: exceeded expectation, met expectation, and did not meet expectation.

Based on SIT, social impact from the network structure in which a student interacts can influence the student's performance. To identify network structures on Twitter, we defined the network boundary by focusing only on interactions about the course through which we conducted the study. Based on the interactions described in Table 1, two students form a link when one mentions the other in a tweet. Therefore, the network is directed since a student may mention another student in a tweet but the other student may not reciprocate the message. We used UCINET 6.1 (Borgatti, Everett, & Freeman, 2002) to compute the network centrality measures of the network. We also developed regression models were to examine how study variables, including network metrics, influence student performance.

[3] Some students posted tweets beyond the required number of postings. However, we found no significant difference in performance between those students and those that participated throughout the study period (i.e., those that earned 5 or the full 6 extra credit points).

4 Results

4.1 Quantitative Analyses

To answer the research questions, we conducted ANOVA tests to examine student performance across discussion platforms. The average performance of students in the treatment group (M = 94.23, SD = 9.50) was significantly higher than those in the control group (M = 78.95, SD = 20.97) (see Table 2). The ANOVA result indicates a significant difference in performance between participants in the treatment group compared to those in the control group over the study period ($F(1, 163) = 40.72$, $p < .05$, $\eta^2 = 0.20$). Minding the unequal sample size across the discussion platforms, we conducted two non-parametric tests, the t-test and Kruskal-Wallis test, to examine participants' performance across platforms. Both analyses confirmed the findings from the ANOVA results (see Tables B1 and B2 in Appendix B). Hence, we use the ANOVA results to test differences in this paper. These analyses address RQ2 (the relationship between using a collaboration tool and student performance) and shows that students in the treatment group (Twitter) performed better than those in the control group (Moodle).

Table 2. ANOVA Result for Performance

Performance	Treatment (Twitter)			Control (Moodle)		
	N	Mean	Std. dev	N	Mean	Std. dev
Final grade	103	94.23	9.50	61	78.95	20.97
Total	N = 164		Mean = 88.54		SD = 16.53	
	$F(1,163) = 40.72$, $p < 0.05$, $\eta^2 = 0.20$					

To further review possible sources of variance in the performance across discussion platforms, we conducted several exploratory analyses. First, we used a 4×2 ANOVA to explore performance across course sections (four levels) on discussion platforms (two levels). Table 3 summarizes the descriptive results. The results show a significant difference in performance across class sections ($F(3,163) = 7.49$, $p < 0.05$, $\eta^2 = 0.12$). Post hoc analysis using Fisher's least significant difference (LSD) test indicated that the pairwise difference in grade (performance) between sections was significant between the higher level courses and the lower level courses (see Table B3 in Appendix B for a detailed account of mean performance differences across each section).

Table 3. Performance by Discussion Platform and Course Section

Course section	Discussion platform	Mean grade	N	Std. deviation
1: Fourth-year students	Moodle	88.88	4	7.37
	Twitter	96.72	26	5.47
	Combined	95.67	30	6.23
2: Third-year students	Moodle	85.04	3	8.24
	Twitter	96.78	31	3.99
	Combined	95.75	34	5.48
3: Second-year students	Moodle	77.99	28	21.48
	Twitter	92.78	24	6.74
	Combined	84.82	52	17.89
4: First-year students	Moodle	77.73	26	22.86
	Twitter	89.24	22	16.85
	Combined	83.01	48	20.94
$F(3,163) = 7.49$, $p < 0.05$, $\eta^2 = 0.12$				

Notably, on average, students in sections 1 (M = 95.67, SD = 6.23) and 2 (M = 95.75, SD = 5.48) performed better than those in sections 3 (M = 84.82, SD = 17.89) and 4 (M = 83.01, SD = 20.94). Further, the unequal size or number of participants in each course section did not seem to have an influence on performance. Even when participants in the treatment condition of some sections of the course were fewer than participants in the control condition, the performance of those in the treatment group (for Twitter: section 1: M = 96.72; section 2: M = 96.78; section 3: M = 92.78; section 4: M = 89.24) was consistently higher than those in the control group (for Moodle: section 1: M = 88.88; section 2: M = 85.04; section 3: M = 77.99; section 4: M = 77.73). Hence, the results suggest that performance improves as students mature. Additional pairwise comparisons (see Table B3 in Appendix B) show which pairwise differences were statistically significant and the direction of such differences. Furthermore, an additional review using social network analysis (SNA) (see Section X) showed specific patterns of interactions in the more mature groups that may further explain such differences beyond the students' maturity level.

To explore RQ1 (whether the collaboration platform influenced engagement), we examined students' participation over the study period by analyzing variances in their performance scores using a 3×2 ANOVA. Table 4 presents the breakdown of participation intensity (three levels: exceed, met, and did not meet expectations) across discussion platforms (two levels: Moodle, Twitter). The results indicate a significant difference in performance between highly active participants compared to those that participated for less than half of the study period or did not post the minimum required postings per week over the study period $F(2,163) = 26.72$, $p < 0.05$, $\eta^2=0.25$.

Table 4. Engagement (Participation Intensity) and Performance

Participation intensity	Platform	Mean grade	N	Std. deviation
Exceeded expectation	Moodle	93.68	19	2.44
	Twitter	97.80	47	3.52
	Combined	96.62	66	3.73
Met expectation	Moodle	85.74	21	2.82
	Twitter	96.17	19	3.92
	Combined	90.69	40	6.25
Did not meet expectation	Moodle	58.82	21	25.02
	Twitter	88.68	37	13.48
	Combined	77.87	58	23.32
$F(2,163) = 26.72$, $p < 0.05$, $\eta^2 = 0.25$				

Although the ANOVA results indicate mean differences in performance and participation intensity between platform groups, we did not know how these variables relate to each other. Hence, we regressed interaction effects and the independent impact of platform group and participation intensity on performance. As Table 5 shows, we found participation intensity and the interaction between participation intensity and platform group to have significant impact on student performance. The negative relationship between participation intensity and performance shows that amount of content posted was not an indicator of good performance. However, the result also shows that the collaboration platform used can afford participation intensity to improve performance. This relationship model explains 52 percent of the performance differences and still leaves the question of how a collaboration platform interacts with participation intensity to influence student performance.

Table 5. Model Estimates for Performance

Variable		Estimate (Std. dev)
	Constant	119.67** (8.020)
Group	Group	-7.25 (4.585)
Participation intensity	Intensity	-26.37*** (3.765)
Interaction	Group*Intensity	9.77*** (2.258)
Adjusted R^2	0.52	
*** = p < 0.01; ** = p < 0.05; * = p < 0.10		

The results in Tables 3, 4, and 5 answer the first two research questions. RQ1 asks if the collaboration platform (Twitter vs. Discussion Board in Moodle) influence students' academic engagement. The results in Tables 4 and 5 indicate that students in the Twitter group were more engaged in their academic tasks than students in the Moodle group. RQ2 asks if using Twitter in academic discussions is associated with student performance. Tables 2, 3, and 4 show that students in the Twitter group consistently performed better than their colleagues in the Moodle group. To further examine how the platform dynamics on Twitter can influence participation intensity and performance, the third research question (RQ3) asks if social impact theory can explain the observed network structure in Twitter's discussions. Below, we investigate the network structure of the Twitter discussions using SNA.

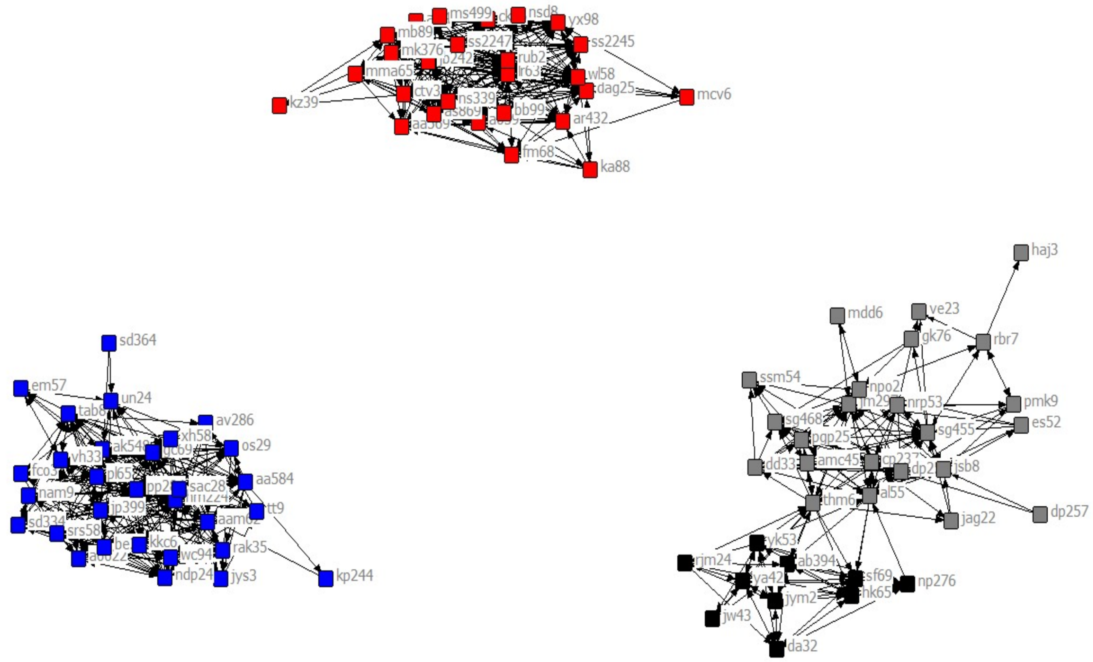
The first rule of SIT suggests that social impact results from a multiplicative effect of strength (betweeness), immediacy (closeness), and number (degree centrality), which informed our decision to run a multiple regression analysis. Regression of the three classic social network measures (degree, betweeness and closeness centralities) on student performance revealed the results in Table 6 below. Consistent with the approach used in prior research (Susarla, Oh, & Tan, 2012), we also conducted and used log transformations on all three centrality measures in the regression analysis as a way to check for the possible skewness in the standard deviation of the centrality measures. We observed no significant difference in the estimates for both models, which suggest that there was no source of error that may be related to skewness in the standard deviation of the network measures. The mean values for each centrality measure were (M = 0.93, SD = 3.11), (M = 2.32, SD = 0.62), and (M = 12.67, SD = 6.93) for betweeness, closeness, and degree centralities, respectively. As Table 6 shows, we found all the centrality measures to significantly affect student performance. These results indicate that students' structural position in their communication network can influence their performance.

A student's betweeness score increases as the student links up with highly connected individuals in disconnected sub-networks in the overall class network. Such a student can tap into ideas from different groups of students. Post hoc analysis of the regression results indicated that students with high betweeness scores performed better (M = 86.20, SD = 30.61) than those with low betweeness score (M = 79.43, SD = 34.02). A student with a high closeness score can easily get to other students in the network to exchange information. In other words, a student that others could access easily would have a high closeness score. Our results show that students that scored high on closeness centrality performed better (M = 86.07, SD = 30.45) than those that scored low (M = 80.57, SD = 33.71). A student's degree centrality score increases when the student has more links than other students do in the network. Such a student becomes highly influential and popular in the network. We found that students that scored high on degree centrality performed better (M = 87.42, SD = 30.13) than those that scored low (*M* = 79.49, *SD* = 33.77). We discuss additional implications of these relationships between network structures and performance in Section 5.

Table 6. Model Estimates for Network Measures

Centrality measures	Estimate	Std. error
Constant	0.00	217.82
Betweeness	0.20**	9.00
Closeness	0.30***	48.25
Degree centrality	-0.36***	4.33
Adjusted R^2	0.14	
*** = p < 0.01; ** = p < 0.05; * = p < 0.10		

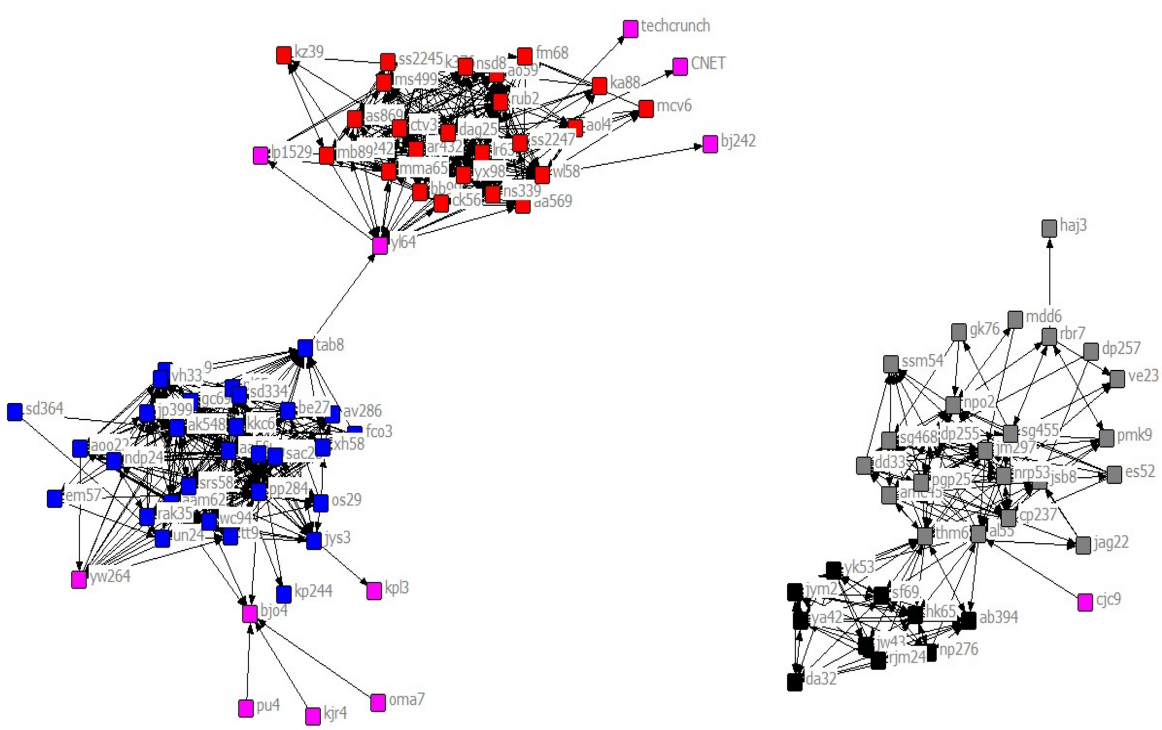
We also examined the actual network structure of the communication links across all sections of the course included in the study (see Figure 1 and 2). Interestingly, higher sections of the course (sections 1 and 2, noted with red and blue nodes, respectively) in Figure 1 had high interconnection among course students. However, we observed cross-links between the lower level course sections (i.e., sections 3 and 4, noted with black and grey nodes, respectively). This observation indicates that first-year and second-year students engaged in communication about course content with peers from other sections of the class.



Color legend: Red=Section 1, Blue=Section 2, Black=Section 3, Grey=Section 4

Figure 1. Network Structure for Only Study Participants

When we include all the communication links about all the courses, some interesting patterns emerge. Figure 2 depicts a network of all the communication links among every individual, including students and non-students.



Color legend: Red=Section 1, Blue=Section 2, Black=Section 3, Grey=Section 4

Figure 2. Network Structure for All Twitter Participants

Pink nodes were individuals that did not register in the course through which we conducted the study. First, we observe a link between the higher-level sections (i.e., third-year and fourth-year sections). Second, a closer look at the connection between the higher-level sections indicates that the incident node was a student not registered in the course through which we conducted the study. Third, we observe communication from senior students with technology companies such as CNET and Techrunch, which shows that Twitter can help expand conversations beyond the classroom.

4.2 Comments from Participants

Examining the discussion content suggests that students liked Twitter's flexibility, especially in that it allowed one to engage with other users on it at any time and place. Most tweets came from locations where students were exposed to phenomena related to the concepts taught in class, which the following comments note:

> *Most of the tweets I posted in the earlier weeks were during lunch break conversations at the Subway across from the school [campus]….* (Student21)

> *The joy of using this tool [Twitter] is that I was able to participate in class related discussions from anywhere, anytime without the need for structured logins and vpn connection authentications….* (Student37)

> *I shared my postings while on spring break…how cool is that….* (Student46)

> *I really like to surf the web at my leisure and use new cool tools…. The ability to use Twitter for class discussion was simply cool!* (Student94)

Participants generally expressed delight in the ability to use Twitter for course discussions rather than only discussing the course content in the classroom:

> *I always used Twitter and other social media technologies during class with fear, but knowing that I can use Twitter in class for class stuff makes me feel more comfortable to learn with a tool I like to use.* (Student128)

The comment shows that students crave SMTs not as a distraction but as a way to connect with content and their peers. As we note in Section 4.1.1, high degree centrality measures in the network demonstrated the intensity of students' participation. The fact that many students want to use SMTs may explain why at least one-third of participants exceeded the expected participation threshold. More so, participants in the treatment group dominated class discussions. Participants in the treatment group became fond of Twitter's flexibility and immediacy and initiated discussions on their "new findings" about the topic of discussion for the week in each class. Some students often posted about eight tweets per week instead of the three that we required.

In the later part of the semester, we observed that participants in the treatment group acknowledged the quality of input (e.g., articles posted, soundness of ideas presented) shared by other students, which the tweets below demonstrate:

> *@Student63 #Student98 #sec2 #wk10 Good article. I believe that the lifecylces of brand or products are getting shorter*

> *@Student56 #Student3 #sec1 #wk12 great article! it is true that IT is involved in every facet of an organization. Fostering open comm. is key*

> *@Student9 #Student2 #sec3 #wk13 Nice article !! I think that business and IT are no longer two different entities. SOA is the enabler for the same*

Participants also noted that, since they received strict instructions about what to discuss using the designated hashtags for the experiment, other discussions developed beyond the topics discussed in class. The new alliance formed among members in the treatment group became useful. For instance, one of the participants' friend needed help with selecting the best specifications for a computer for business. Once the participant posted the question on Twitter, suggestions from the class provided several useful ideas that the participant's friend considered to make the final purchase. Other similar stories covering several topical areas emerged throughout the semester.

Students described conversation on Moodle as overly and strictly collegial and as carefully articulated:

> *I felt I needed to write a very structured essay about how the technology we learned that week affect our society. The one page paper is the worst part of my day every week.* (Student05)

> *I spent a lot of my time worrying about my grammar than the actual concept I'm trying to write about.* (Student07)

When questioned about their experience throughout the study period, participants in this group described it as informative and educative but with so much structure that it felt like a classroom outside the actual class. Most of the participants in the group shared this sentiment. In addition, students expressed the need to have a more enjoyable experience that would encourage students to want to share rather than doing so to fulfil a requirement:

> *Signing in to Moodle every time to post messages was not fun at all. It would be nice to be able to post those messages from any other application without having to sign in….now that would be fun and I will be all over it!!!* (Student01)

> *I think it'll be much more interesting if we get to freestyle our writing to reflect exactly what we feel about technology as we see and experience it daily.* (Student10)

Some participants noted that more than two-thirds of the users stopped participating because they simply did not enjoy using the discussion board to discuss ideas they were going to discuss in class anyway. With the low enjoyment students derived from Moodle, students in the higher-level classes were not particularly interested in using it compared to those in the lower level classes. However, the postings were noticeably structured, which confirms that discussion forums promote cognitive presence (Schroeder et al., 2010).

5 Discussion

In this study, we explored how collaboration platforms influence students' academic engagement and whether a relationship between Twitter use in academic discussions and students' performance exists (RQ1 and RQ2, respectively). Our findings suggest that Twitter and Moodle influenced students' performance in different ways. Since using Twitter was associated with better student performance, we conducted additional exploratory analyses and SNA to examine the performance differences across course sections. Specifically, we looked at network structure and conversation trends on Twitter in relation to student performance (RQ3). By no means do we suggest that Twitter use has a direct effect on students' performance since studies abound that show performance as a function of individual prerequisites, context, and processes with the inclusion or exclusion of technology (e.g., Butcher & Visher, 2013; Chemers, Hu, & Garcia, 2001).

Consistent with the expected relationships that engagement theory postulates (Kearsley & Shneiderman, 1998), we found student academic engagement (participation intensity) on Twitter to be associated with performance, which positively answers the second research question. Further analyses show that third-year and fourth-year students performed better than first-year and second-year students on both platforms (see results in Table B3 in the Appendix, which compares mean performance across each group and shows statistically significant differences in most comparisons. In accordance with the research model posited in this study, for Twitter users, better performance was associated with high information exchange intensity. For Moodle users, greater familiarity from previous experience with learning management systems could plausibly explain the performance differences we observed between third-year and fourth-year students compared with first-year and second-year students. Another explanation could be that third-year and fourth-year students are more mature and value the interactions better than first-year and second-year students who have only recently begun university. We also found that, on average, active participants performed better than their inactive counterparts did. To further understand the nature of the relationship between Twitter use and student performance, the content analysis of student conversations on Twitter revealed that students who used Twitter engaged more with the course materials compared to the students in the control group. This result contributes to the body of literature that seeks to understand the impact of SMTs on student learning and performance. In addition, active participants (those that participated in discussions for at least more than half of the study period), both in the control and treatment groups, performed better compared to those that were inactive. This result is consistent with engagement theory.

From a social network perspective, we found various conversation patterns across course sections, which is indicative of affective learning (Bloom, Englehart, Furst, Hill, & Krathwohl, 1956) among students who interacted with others outside their classes about how concepts learned in class apply in day-to-day applications. The findings also provide evidence of the multiplicative social forces that constitute social impact and, subsequently, influence student performance. Using SNA, we found that the three centrality measures (betweeneness, closeness, and degree centrality) impacted student performance. Students that communicate with people outside their classes score high on betweeness centrality, which potentially improves their learning. According to theory, we observed that the higher the closeness score for each node, the better the performance. Lastly, we found a negative relationship between degree centrality and student performance. We can explain this relationship with SIT's second rule, which suggests that the higher the number of discussants, the less impact each discussant feels. Putting all the results together, we can infer that the popularity of one's communication does not necessarily guarantee success; rather, it is one's location in the network that influences how information flows through the network (RQ3). Since we detected centrality measures only a posteriori, it may be useful to compute these measures a few times during the life of a course (e.g., throughout the semester) to use them for formative assessment. One can speculate that, as students seen themselves in the network at time T1, they can then make amendments to connect with certain nodes for better communication. More importantly, these results confirm the viability of using Twitter as a collaboration platform to foster engagement and performance among university students.

5.1 Limitations

This study has several limitations. The use of a computer-mediated communication platform for the control instead of a using a group without any form of technology (face-to-face discussion) might have led to interactions between the tool and the experimental design. However, we did not deem it appropriate to compare technology-based discussions with non-technology based discussions, nor did we control for the natural face-to-face discussions happening in class.

The unequal number of participants in the experimental groups may have contributed to variations in the data beyond the distribution of the sample itself. The sample restriction, due to the inclusion criteria required to properly execute the quasi-experimental design, consequently limited the number of participants in the control group.

Moreover, given that the instructor structured the course around discussion, the observed student performance may vary across course structure and disciplines. Researchers should bare these limitations in mind in future studies on SMTs' impact.

5.2 Conclusions

This study shows several positive qualities of using Twitter as a pedagogical tool for promoting engagement. More importantly, students engaged in meaningful discussions with references to relevant examples and events unfolding without much input from the instructor. Students mostly held and sustained class discussions rather than the traditional one-way information push from the instructor that "becomes boring relatively quickly, no matter how interactive an attempt employed" as several participants noted.

In analyzing student conversations in Twitter, we found evidence of shared mental models (Leonardi, 2011; Leonardi, 2013) among students, which may have influenced their performance as compared to the groups that used the discussion forum on Moodle. The spontaneity associated with using Twitter makes it accessible and easier to use to seek advice, pose quick questions, and ask for suggestions on concepts that might be confusing. Future studies may focus on examining the direct influence of shared mental models and performance to further develop our understanding on using microblogs for learning.

Conversations on the discussion forum on Moodle, however, indicate that these students extensively analyzed assigned topics. As prior research notes (Schroeder et al., 2010), discussion forums encourage cognitive presence for students and teachers. The result shows that students in the higher-level classes dropped out about halfway through the study partly because they did not enjoy using the platform for discussion. This finding is consistent with the speculated relationship between the use of Moodle and engagement among students and the subsequent effects on performance. Since students in the Moodle group did not enjoy the information-sharing process, they shared less information compared to their Twitter counterparts, which lead to their lower performance. These results draw attention to the need to further explore social technology use for learning to understand the factors responsible for differences in usage patterns across student groups, faculty, and staff classifications. In particular, they show the importance that engagement with a collaborative technology has on learning outcomes.

5.3 Implications for Practice

Our study has implications for developers, educational institutions, and students. The practical implications stem from the premise that the new information age requires organizations to keep up with the advanced-level knowledge of its customers. In the case of students, one needs to understand that this new generation of learners engages differently with learning materials. Developers should explore how to integrate social media technologies into learning management systems to sustain student adoption and enjoyment in the learning process. One can implement incentives at the institutional level to increase the use of social technologies in the classroom. Furthermore, one should create guidelines on how to use social media to improve the educational experience of all stakeholders (especially students, faculty, and administrative staff) involved. Echoing Roth and McCully's (2010) recommendation, when implementing social media technologies, one should so deliberately and simply enough for students and faculty members to grasp. After all, the famous technology adoption model (TAM) (Venkatesh, Morris, Davis, & Davis, 2003) posits that the ease of use of an information system determines the extent to which it will be implemented and used. Hence, when implementing innovations to effectively use any form of social media in the classroom, one must consider how easily relevant stakeholders will use them. Finally, results from the SNA indicate that students who use Twitter have the opportunity to collaborate in and across multiple networks and, consequently, improve their performance. This finding validates the claim we make earlier that Twitter can help students collaborate and share knowledge. Comments from participants in both groups also support this claim. Twitter can positively contribute to student engagement and performance when used appropriately as a collaboration platform in university courses.

5.4 Implications for Research

In addition to its practical merits, this study serves both as motivation and input to extending student academic engagement-related research. We need further work on a composite theory of engagement that delineates connections between academic and non-academic activities. Most importantly, we need a process-level approach to understand the cognitive and structural underpinnings responsible for engagement in a technology-mediated learning environment. Similar to the work done on engaging university-level students (Harasim, Hiltz, Teles, & Turoff, 1995; Hiltz, 1986), we need more empirical research to understand strategic implementations of social media technologies based on engagement theory.

This study analyzes only how microblogs and discussion forums functionalities can contribute to students' learning experience. Future studies may extend the framework to other social media technologies to help teachers identify potential learning impact of the different technologies for better incorporation into any course.

5.5 Contributions

We summarize the paper's contributions as follows:

1. It provides empirical evidence of the relationship between Twitter usage and student performance and its effectiveness in promoting student engagement with course materials.
2. It demonstrates how Twitter can foster engagement with students in and beyond the classroom.
3. It shows how the structure of the social network may explain students' performance and suggests that one could use dynamic visualizations of network structures for formative assessment.

As our results highlight, we should encourage rather than discourage educators to use Twitter or other social media technologies in the classroom. Creating fear in students because of their engagement with social media technologies might be a generational issue that higher learning institutions need to address. The current information age requires new approaches to engage students in their learning process, and, as such, we should encourage rather than stifle technologically induced advancements in how we achieve it. It may just be that, when dealing with the impact of new SMTs on outcomes, we may need to recognize that we are, in fact, dealing with a new generation of learners.

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Appendix A: Instructions

Objective

The objective of this activity is to encourage participation of students with materials taught in class. Students are required to participate by posting short messages or questions that relates events they encounter in their everyday activity to concepts taught in class. As a result of the spontaneous nature of the participation, students are required to use **TWITTER** for this activity. Instructions on how to send and respond to tweets for this activity are described as follows. If you do not have a twitter account, you can easily create one by following this link: http://twitter.com/

Chance to Draw and Extra Credit and Posting Instructions

Participants are required to post at least one message (send a tweet) per week and respond or critique (either by re-tweeting or replying) at least two postings from other participants in the class. Your participation will automatically enter you into a random chance to win gift cards in the amount of $25, $50 and $100 to Barnes and Noble or Amazon. The extra credit is accumulated by summing up half a point every week that you participate, which means you can receive up to six points by the end of the semester toward your final grade if you participate throughout the semester.

Sending Procedure

The following predefined hashtag syntax must be used to send tweets:
#studentId #class #weekNumber e.g., #abc1 #is350 #wk5
A sample tweet (post) in the fifth week [wk5] by a student, with student id [abc1], taking the computers, science and ethics class [is350] is:
#abc1 #is350 #wk5 The mother that shot the intruder in Oklahoma is justified under the Kantian theory http://news.yahoo.com/okla-woman-shoots-kills-intruder-911-operators-okay-091106413.html

NOTE: You may include a link to the source of information in your original tweets. Re-tweet or reply may or may not include a link.

Responding Procedure

In order to save space when you reply tweets, you may use the student id of the person you are responding to instead of the username of the poster that Twitter provides in your re-tweet. For instance, responding to the post above can be written this way:

@abc1 #xyz2 #is350 #wk5 I agree that Kantian theory is applicable just as well as social contract theory. This identifies your tweet so that it can be found as described below.

Access to postings

In order to respond to tweets, you can retrieve tweets posted to a weekly discussion by searching for the predefined hashtags i.e., #classid #weekNumber e.g., #is350 #wk5

Also, a link to a dashboard that contains all the tweets is provided on a dedicated server available on the class website.

IMPORTANT!!!!

In order to track your tweets and award your weekly points, you need to ensure that you include the predefined hashtags in **ALL** your tweets:#studentId #course #weekNumber e.g., #abc1 #is350 #wk5

Appendix B: Additional Analyses Results

Table B1. Kruskal-Wallis Median Test

		Discussion platform	
Median score = 94.17		Moodle	Twitter
Performance	> Median	8	74
	<= Median	53	29
$\chi 2(1, 164) = 59.36$, $p = 0.000$, $\eta 2=0.364$			

Table B2. T-test Results

Performance	Treatment			Control		
	N	Mean	Std. Dev	N	Mean	Std.Dev.
Final grade	103	94.23	9.50	61	78.95	20.97
EVA	t-value = 6.38, $p < 0.05$					
EVNA	t-value = 5.37, $p < 0.05$					
EVA = equal variances assumed						
EVNA = equal variances not assumed						

Table B3. Multiple Comparisons Using LSD

(I) section	(J) section	Mean difference (I-J)	Std. Error	Sig.
Fourth year	Third year	5.65869	3.56092	.114
	Second year	8.35284*	4.22570	.050
	First year	12.88474*	3.71420	.001
Third year	Fourth year	-5.65869	3.56092	.114
	Second year	2.69416	3.72983	.471
	First year	7.22605*	3.13852	.023
Second year	Fourth year	-8.35284*	4.22570	.050
	Third year	-2.69416	3.72983	.471
	First year	4.53190	3.87644	.244
First year	Fourth year	-12.88474*	3.71420	.001
	Third year	-7.22605*	3.13852	.023
	Second year	-4.53190	3.87644	.244
* The mean difference is significant at the 0.05 level.				

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