Unveiling engagement patterns of Yellowdig users: analysis of learning behaviors in an online undergraduate course

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Abstract

Purpose – In online courses, asynchronous discussions are a common course activity that helps build community, explore concepts and provide an opportunity for formative feedback.

Design/methodology/approach – This case study explored engagement patterns in the Yellowdig platform used in an introductory-level chemistry class. Data were examined using Z scores, multiple regression, ANOVA and non-parametric testing to identify the impact of student activity on discussion and summative assignment grades.

Findings – Profiles of learner engagement were identified using the interactive, constructive, active and passive (ICAP) cognitive engagement framework. These profiles can be used as predictors of student performance. Moderately high and moderately low activity groups scored significantly better than low or significantly low activity groups.

Originality/value – This study unveils distinct learner engagement profiles linked to performance outcomes, providing valuable insights for online course design and pedagogical practice.

Keywords Asynchronous online discussions, Learner engagement, Behavior patterns, ICAP, Social learning

Paper type Research paper

Introduction

Online undergraduate course offerings are a popular option among undergraduate students (National Center for Education Statistics, 2021). Grounded in social constructivism theory (Hammond, 2005), discussion activities in online courses are a common activity to combat isolation, provide active and interactive learning opportunities, and to establish a community of inquiry (Ratan *et al.*, 2022). Research supports a positive association between learner engagement in asynchronous discussions and their content mastery (Jo *et al.*, 2017). However, there are moderating variables such as the learner's characteristics, the course and discussion structure, and the instructor. Where students are graded based on their initial and reply posts, it can be easy to box-check, limiting authentic conversation (Hunzer, 2014). The number of posts read was not a performance predictor, meaning that new postings were more valuable than reading more posts (i.e. lurking) (Palmer *et al.*, 2008). This is important as a standard set of engagement expectations may hinder student engagement and content mastery. Recent literature has encouraged practitioners to question how we evaluate participation in asynchronous discussions (Bailie, 2020).

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Social learning in asynchronous discussions

Social constructivism theory outlines the collaborative nature of learning, suggesting that student learning is supported through active construction of their understanding through social interactions with their peers and instructor (Greeno *et al.*, 1996). Within asynchronous discussions, several frameworks have been used to explain learner engagement, including Community of Inquiry, Self-Determination Theory, and Transactional Distance Theory.

Social learning can be evaluated through the lens of the Community of Inquiry framework, described by teaching, social, and cognitive presences (deNoyelles *et al.*, 2014). The presences are positively related to each other, with each presence affecting the other (Kozan and Richardson, 2014; Zhu, 2018). Specifically, social presence theory proposes that communication is more effective when individuals feel a sense of connection and social presence with others (Cui *et al.*, 2013). In the context of online discussions, social presence is a measure of the degree to which participants feel like they are communicating with other real people rather than just interacting with a computer. Through social presence, learners and instructors project their personality into the learning community and whether others can connect with them. Social presence has been shown to mediate the relationship between active learning tasks and perceived content mastery (Ratan *et al.*, 2022).

Social learning in asynchronous discussions can also be viewed through the lens of Self-Determination Theory. Self-determination theory posits that people are motivated by three innate psychological needs: autonomy, competence, and relatedness. In the context of online discussions, students are more likely to engage if they perceive the discussion as relevant to their learning goals, if they have some degree of control over the discussion topic or structure, and if they feel a sense of competence in their ability to contribute meaningfully to the discussion (Ryan and Deci, 2020). Self-determination can influence engagement behaviors (Rosen and Laubepin, 2022), which may explain why some students contribute more to the knowledge-building in discussions than others (Avcı, 2020).

Additionally, social learning in asynchronous discussions can be explored through the lens of Transactional Distance Theory, which suggests that the degree of psychological and communication space between learners and instructors affects the learning process. In the context of online discussions, instructors should strive to create a sense of community and collaboration in the online classroom, even in the absence of physical proximity. Some strategies for achieving this that have been explored by researchers and practitioners include the use of videos or audio recordings in discussions (Gurjar, 2020) and the use of assigned roles in discussions (Yilmaz and Karaoglan Yilmaz, 2019), which personalize the learning experience. Both perceived transactional distance and perceived social presence predict knowledge-sharing behaviors in online discussions (Karaoglan Yilmaz, 2017). As outlined in the peer support hypothesis, strong peer connections in asynchronous online learning limit isolation and thus may encourage course persistence (Faulconer *et al.*, 2018; Sinclair, 2017).

Social learning in asynchronous discussions does not happen inherently. Community must be crafted through course design and curated by the instructor to promote student social presence and establish instructor social presence, to establish nurturing conditions (e.g. inclusive structures, supporting teaching behaviors, and an engaging learning environment) to promote self-determination, and to provide opportunities to reduce the virtual space between learners and the instructor to reduce transactional distance. To this end, instructors implement a variety of research-based strategies in asynchronous discussions to promote social learning (Aloni and Harrington, 2018; Sadowski *et al.*, 2017). Learner behaviors can influence discussion engagement patterns. For example, some students may feel free from peer pressure when engaging in discussions asynchronously online (Steyn and Van, 2017) while others may be concerned about presenting a positive virtual image in the online learning environment and thus be reluctant to engage (Ng *et al.*, 2012). Beyond the influence of the basic design and prompt for a discussion (which inherently influences engagement patterns), the instructions, deadlines, and scoring format (e.g. rubric) can also influence engagement behavior patterns (Giacumo and Savenye, 2020). Push notifications can promote continued engagement for some students while others dislike them (Garbrick, 2017). Instructor participation (e.g. instructor's social presence and teaching presence) and class size can also influence engagement behaviors in asynchronous discussions (Parks-Stamm *et al.*, 2017). Receiving instructor feedback is a noted motivation factor in online learning environments (Cole *et al.*, 2017).

Engagement frameworks

While many research papers focus on relationship networks, there is some attention in the literature to the importance of the timing of events in asynchronous online discussions (Chen and Poquet, 2020). Each learner brings their own previous knowledge and experiences, opinions, and ideas to the discussion. Each learner also possesses unique habits, interests, communication styles, and availability. For many reasons, students may prefer to engage early, late, or periodically. For example, one student may "listen" before engaging while another may prefer to start the conversation as their work schedule permits more flexibility earlier in the week. Students who post early or throughout the discussion received privileged engagement while students whose posts were not timely or occurred in a compressed time frame did not tend to garner as many responses (Chen and Huang, 2019; Garbrick, 2017). This suggests more attention is needed to understand engagement patterns in asynchronous discussion patterns so that instructors can better design scaffolding and provide facilitate to support meaningful participation.

The Interactive, Cognitive, Active, and Passive (ICAP) engagement framework has been applied in analyzing student learning in online courses (Chi and Wylie, 2014) and specifically in online discussions (Gorgun *et al.*, 2022). Passive engagement is minimally helpful in supporting learning, active engagement allows students to fill gaps in understanding, constructive engagement involves generation of new information that may be transferable, while interactive engagement promotes synthesis and new ideas. Some studies applying ICAP to online discussions use qualitative methods that are time-intensive (Wang *et al.*, 2016). Other studies use machine learning processes to analyze cognitive engagement using a modified ICAP framework (Gorgun *et al.*, 2022). However, it would be helpful for instructors to quickly evaluate learner engagement behaviors without the time investment of qualitative analysis or specialized skills needed for applying machine learning. Many learning management systems (LMS) have built-in discussion forum areas and many external tools can be integrated into the LMS, which can be a source of learner analytics for evaluating learner engagement. Multiple research studies have reported evidence to link cognitive behaviors in asynchronous discussions to learning outcomes (Galikyan and Admiraal, 2019; Raković *et al.*, 2020).

Yellowdig

Yellowdig is an educational technology tool that allows students to build active, social, and experiential learning communities online (a closed social media platform). The platform is designed to feel like social media, allowing students to share original or found content (e.g. photographs) on a feed. Posts can be reacted to and commented on. Students earn points through a variety of actions, not just the standard "initial post and reply post" engagement. The instructor can manipulate unique point-earning pathways for students, including how many points students earn for an initial post, a reply post, gaining a reply post on their initial post, receiving up-votes, and instructor badges. The instructor establishes a minimum number of points a student must earn in a points-earning window and the platform clearly displays progress to the student on their dashboard. A leaderboard is also present on the right side of the feed, showing the top contributors in the discussion based on the points system (without displaying their earned points). The instructor can also allow a margin for earning additional points in a window that can roll over so that students can compensate for a week where they did not meet the minimum engagement expectations. The instructor badges can be designed by the instructor according to whatever scheme they choose whether it is for social encouragement, cognitive presence, or some other motivator. Within the feed, a search feature, the use of topic tags, as well as the use of hashtags within initial and reply posts can help organize topics. An example anonymized Yellowdig post is shown in Figure 1. The platform has been shown to benefit student learning through increased engagement, satisfaction, content learning, and self-regulated learning (Whiteside and Ensmann, 2023; Ensmann and Whiteside, 2023; Martin *et al*., 2017).

Research questions

Asynchronous online discussions are a vital component of online learning environments. It is important to understand how students approach asynchronous discussions as there are numerous moderating and mediating variables (Figure 2). The purpose of this paper is to explore the following research questions:

RQ1. What engagement activities in Yellowdig correlate to achievement scores on discussions and summative assessments?

RQ2. Can learner engagement in Yellowdig be categorized into profiles based on engagement using the ICAP framework?

RQ3. To what extent does the engagement profile predict achievement of engagement expectations?

Methods

To explore learner profiles when using the Yellowdig platform for asynchronous discussion in an online undergraduate course, we used a secondary data set from the LMS and the Yellowdig platform. The course investigation is considered a single case study (Willis *et al*., 2007). Previous research has explored clustering of student behaviors in asynchronous learning environments into distinct learner profiles (Kovanović *et al*., 2015; Lust *et al*., 2013; Prestridge and Cox, 2023).

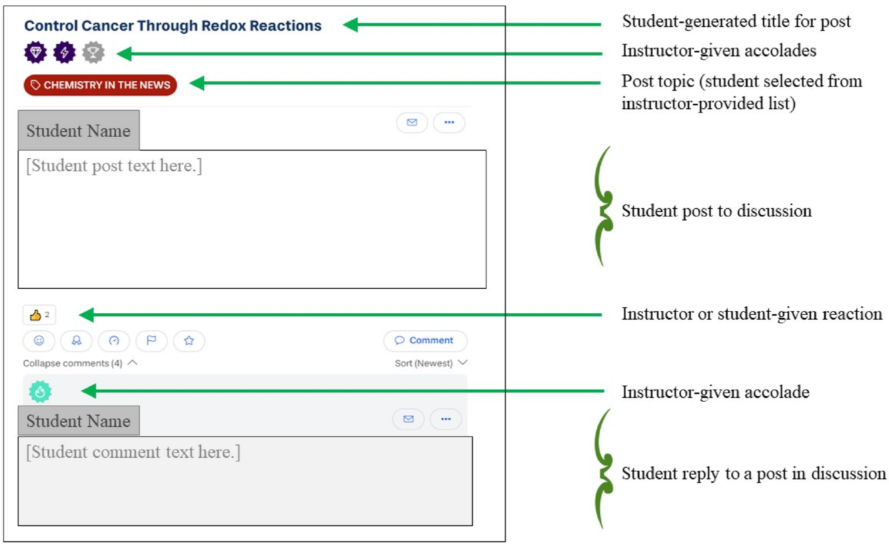

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Figure 1. Example layout in Yellowdig

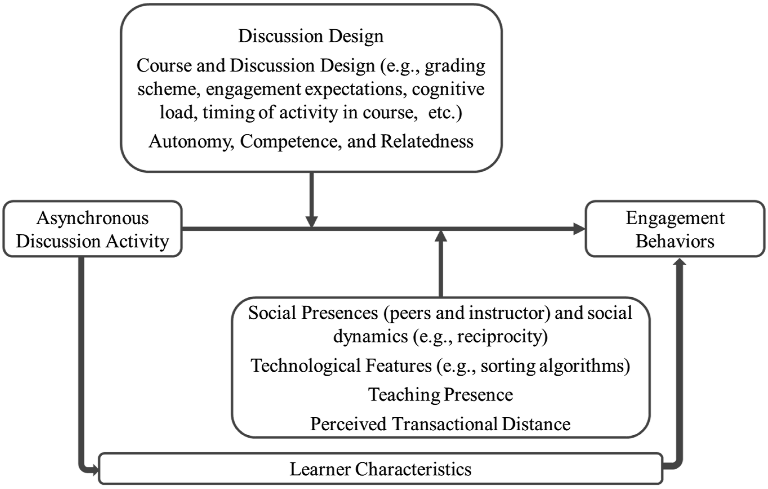

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Figure 2. Conceptual framework for learner engagement in asynchronous online discussions

Context

This study was completed by evaluating an undergraduate general chemistry course at a medium-sized private institution in the United States where asynchronous online courses run on a 9-week semester. The LMS used was Canvas and the discussions took place in Yellowdig during the study (May 2023 through July 2023). To limit instructor influence as a moderating variable, data was collected from sections taught by a single instructor.

Students were required to engage in nine discussion activities throughout the semester. The initial post was uploaded and graded separately for content knowledge, digital literacy (e.g. source citation), and communication. Initial posts were worth 10% of the overall course grade (1.11% each). Engagement in the Yellowdig platform was graded once across the term (15% of overall course grade), with an expected points earning threshold each week and automatic pass back of grades to the LMS. Students earned points for making posts, replying to posts of others, receiving comments on their posts, and receiving upvotes (emojis). Additionally, students earned points through earning accolades (badges) assigned by their instructor. Some accolades aligned with general education competencies of the institution (e.g. digital literacy, scientific literacy, cultural literacy) while others were designed to promote strong cognitive and social presence (e.g. bridging).

Data

Yellowdig learning analytics and LMS data were used to measure engagement. The Yellowdig platform provides robust learning analytics, including reporting individual student progress in an earning window and specific engagement actions for each community member. Specifically, variables based on learner's engagement actions within the Yellowdig platform were extracted (Table 1) and categorized based on the ICAP framework.

Data analysis

Data analysis for 20 students generating 180 weekly discussion grades was accomplished using multiple regression (citing adjusted r squared values) and Pearson's r to evaluate the relationships between student performance and grades. Correlation Coefficients between +35

Table 1. Clustering variables for discussion engagement actions in Yellowdig

Category	Type	Description
Interactive engagement	Reply post count	Number of reply posts made
	Reply post time	Hours before earning window closed
	@ Mentions given	Number of times participant used the @ feature to directly speak to another learner in the community
	Up-votes given	Number of reactions given to peers
Constructive engagement	Initial post count	Number of new posts made
	Initial post time	Hours before earning window closed
Active engagement	Instructor post views	Number of posts viewed shared by the instructor
	Student post views	Number of posts viewed shared by other learners
	Hyperlinks clicked	Number of links shared by anyone in the community that the learner clicked on
Passive engagement	Badges received	Number of badges received from instructor
	Replies received	Number of reply posts on their initial post
	Up-votes received	Number of reactions received by peers
Outcome	Points in earning period	Total number of points earned in the earning window

Source(s): Table by authors

and −0.35 were considered weak correlations. Coefficients between +0.35 and + 0.65 or −0.35 and −0.65 were viewed as moderate relationships. Strong relationships were defined as those between +0.65 and 1.00 or −0.65 and −1.00 (Gay *et al.*, 2009).

One of the main goals of this case study was to determine identifiable engagement profile groups. We were able to identify four engagement profiles (significantly low, low, moderately low and moderately high) based on assigning a z score for each student on each discussion engagement activity which included Reply Post Count, Reply Post Time, Up-votes Given, Initial Post Count, Initial Post Time, Badges Received, Replies Received and Up-votes Received. These z scores were compiled into a composite score which allowed us to identify engagement profiles. The four categories were based on composite z scores and their distance from the mean z score of 0. Categories were (1) lower than two standard deviations below the mean, (2) between −2 and −1 standard deviations below the mean, (3) between −1 and 0, and (4) between 0 and +1. No groups in this case study were above the composite z score of positive 1.

For evaluating differences between groups, ANOVAs and *t* tests were used (Kovanović *et al.*, 2015; Lust *et al.*, 2013). Tukey's honestly significant difference test was performed to evaluate differences among individual pairs of clusters (Kovanović *et al.*, 2015). Post hoc tests for Homogeneity of variance were evaluated using Levine's or Shapiro-Wilk analyses as appropriate. When conditions for parametric statistical tests were violated, Kruskal-Wallis or Mann-Whitney *U* statistics were used to evaluate the research questions. A Bonferroni adjusted alpha level of 0.025 was used to evaluate all *p* values (Gay *et al.*, 2009).

Results

Student performance was examined to determine relationships between student activity in Yellowdig discussions and module discussions and assessment scores (Research Question 1). Data were also examined to identify possible student engagement profiles based on the ICAP framework (Research Question 2). Additionally, a correlation between engagement profile and performance on summative assessment was investigated (Research Question 3).

RQ 1: Student Engagement Actions and Performance

Student activity in discussions and discussion grades were examined based on the Interactive, Constructive, Active and Passive (ICAP) engagement model shown in Table 1.

Interactive engagement factors

Of the interactive engagement factors measured, reply post count, and reply post days before closed showed a moderate significant correlation with high discussion scores (Table 2, Figure 3). Students who quickly made more reply posts tended to get higher discussion scores. The regression model was useful in predicting 53% of the variation between how fast replies were made, number of replies and discussion score.

A similar multiple regression test using Reply Post Count and timing of Reply Posts to predict summative assessment scores yielded only one significant predictor variable. However the relationship between how quickly students posted their first reply showed a weak correlation, $r(143) = 0.16$, $p = 0.0496$. The coefficient of determination was 0.026, accounting for less than 3% of the variation.

Constructive engagement

Constructive engagement actions evaluated in this study included if an initial post was made by students (not replies to others) in a discussion and the timing of the initial post in relationship to the engagement deadline. Students who did not make an initial post ($M = 42.2$, $SD = 64.3$), Mdn, 0 ($IQR = 0–80$) with some commenting to posts of other students showed significantly lower scores than students who made initial posts ($M = 209.8$, $SD = 95.1$), Mdn 227 ($IQR = 140.5–262.5$). The Initial *t*-test showed a significant finding, $t\ (51.7), = -11.65$, $p < 0.001$. However, the Shapiro-Wilk normality test results indicated the distributions were not normally distributed, $p < 0.001$. Due to the identification of non-symmetrical distributions, the Mann-Whitney *U* test was run resulting in a statistically significant finding, $U(N_{\text{Initial post not made}} = 28, N_{\text{Initial post made}} = 132) = 614.5$, $p < 0.001$. Figure 4 visualizes the differences between these two groups. Note that the top boxplot depicts discussion scores for those students who did not make initial posts while the bottom boxplot shows the overall discussion scores of students who made an initial post.

The statistically significant difference indicated that those who made an original initial post tended to score higher on discussion scores than their counterparts who did not do an original initial post and may or may not have replied to the initial posts of other students.

Little difference was noted in summative assessment scores between those who made initial posts and those who did not, Those who did not make an initial post (Mdn = 88.75,

Table 2. Multiple regression: interactive engagement factors and discussion scores

Variable	Estimate	Standard error	DF	*T*-stat	*p* value
Reply post count	36.171	3.081	142	11.738	<0.0001
1st Reply days before closed	13.245	2.978	142	4.4481	<0.0001

Source	DF	SS	MS	*F*-stat	*p*-value
Model	2	554678.96	277339.48	81.779	<0.0001
Error	142	481568.9	3391.3303		
Total	144	1036247.9			

Note(s): Summary of fit:
Root MSE: 58.235
R-squared: 0.535
R-squared (adjusted): 0.528
Source(s): Table by authors

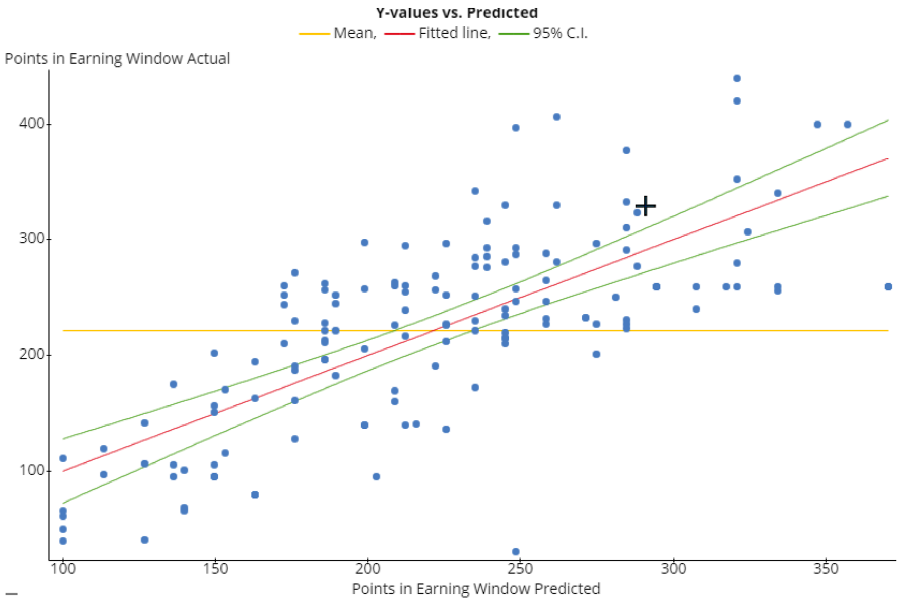

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Figure 3. Interactive engagement factors and discussion scores

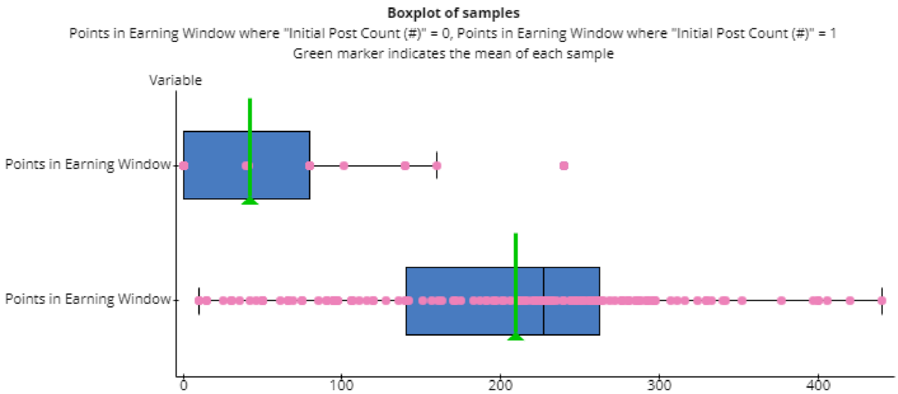

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Figure 4. Points awarded for those who made initial post vs those who did not

(IQR = 78.75–95) scored similarly to those who made initial posts (Mdn = 85, (IQR = 75–93.86) on subsequent summative assessments, $U(N_{\text{Initial post not made}} = 28, N_{\text{Initial post made}} = 152) = 2724.5$, $p = 0.45$.

Making a post earlier in the discussion period was moderately correlated with discussion points awarded in the earning window, $r(150) = 0.40$, $p > 0.001$ (Figure 5).

This result implies that students who posted earlier tended to earn higher points for the discussion period. This relationship was further evaluated using an Analysis of Variance (ANOVA) to determine if there was a difference in discussion scores based on when initial

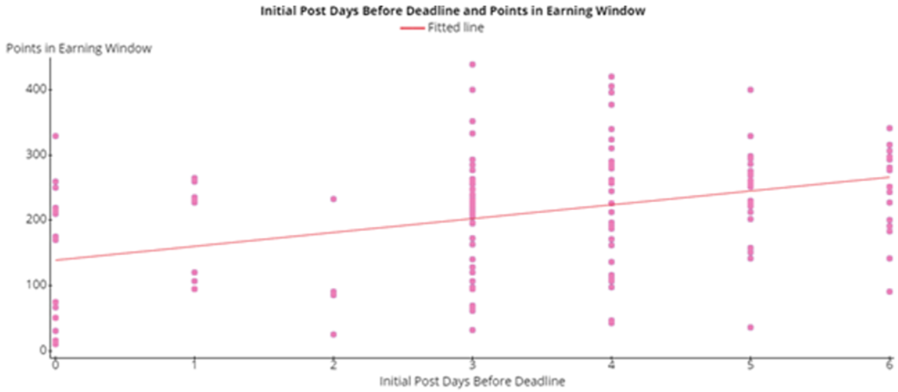

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Figure 5. Relationship between timing of initial post and discussion scores

discussion posts were made. The results, $F(6, 145), = 5.86, p < 0.001$, necessitated a Tukey HSD (Honestly Significant Difference) test which identified significant differences between groups who posted less than three days prior to the deadline and groups who posted earlier. Levene's test for Homogeneity of Variance ($p = 0.08$) indicated variances were within limits for the ANOVA.

Since the data yielded two clear groups, the break point of three days or more before the discussion deadline was further explored by comparing the two major groups; (1) discussion grades for students who posted less than 3 days prior to the deadline vs (2) discussion grades for students who posted three or more days prior to the deadline.

Initial post 3 or more days prior to deadline made a difference in Discussion Points Earned

Students who posted earlier tended to score higher in discussion points than students who posted later in the discussion points earning window. A *t*-test comparing discussion scores of students who posted less than three days prior (M = 138.2, SD = 95.3, Mdn = 106, IQR = 50–227), to deadlines and those who posted earlier (M = 229.7, SD 85.3, Mdn, 244, IQR = 187–280) yielded significant results, $t(47.2) = -4.99$, $p < 0.001$. The Shapiro-Wilk normality test results indicated the distributions were not normally distributed, $p < 0.001$. However, the Mann-Whitney *U* test also resulted in a statistically significant finding, $U(N_{\text{Initial Post <3 days before deadline}} = 33, N_{\text{Initial post 3 or more days before deadline}} = 119) = 1{,}499$, $p < 0.001$. In Figure 6, the upper box plot shows discussion points for those who posted less than three days prior to deadlines while the bottom scores for those who made their initial posts earlier.

Students making initial posts earlier and total posts made during discussions

An additional *t*-test was run to determine if those who made an initial post less than 3 days (M = 2.5, SD = 2.53, Med = 2, IQR = 0–5) before the deadline posted fewer times overall in discussions than those who posted three or more days (M = 3.36, SD = 1.61, Med = 3, IQR = 2–4) prior to the deadline. There was not enough evidence to support the idea that those who posted later posted fewer times overall, $t(39.52) = -1.76$, $p = 0.086$. The Shapiro-Wilk normality test results indicated the distributions were not normally distributed ($p < 0.001$). A Mann Whitney *U* test was run to evaluate the differences $U(N_{\text{Initial Post <3 days before deadline}} = 33, N_{\text{Initial post 3 or more days before deadline}} = 119) = 2{,}122$, $p = 0.07$. The results suggest there is not enough evidence to reject the idea of no difference.

Regarding the relationship between summative assessment scores and how early a student posted, there was a weak correlation between making an initial post earlier and higher summative assessment scores, $r(150) = 0.28$, $p < 0.001$ (Figure 7).

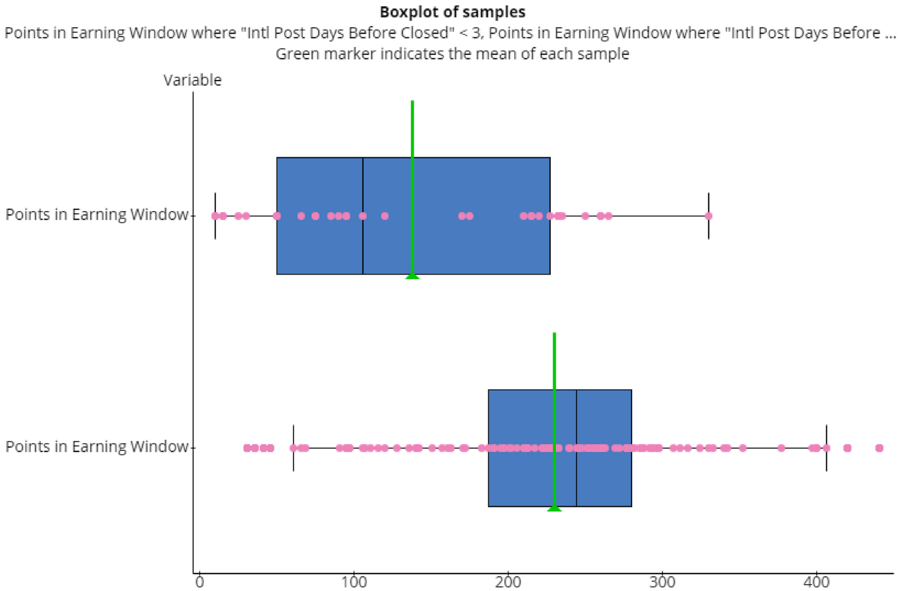

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Figure 6. Initial post less than 3 days vs 3 or more days and discussion points earned

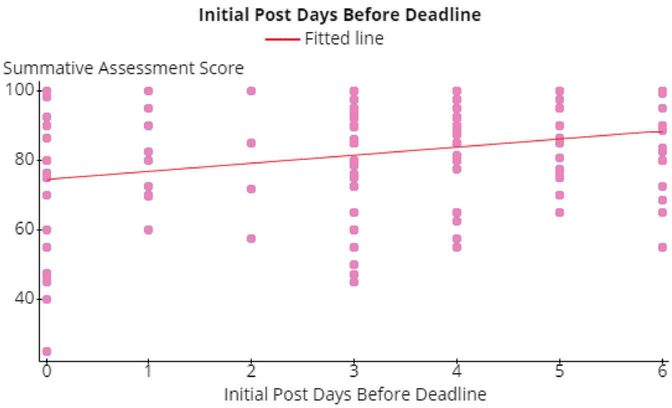

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Figure 7. Relationship between timing of initial post and summative assessment performance

The results show positive relationships between making initial posts earlier in both discussion scores (moderate) and summative assessment scores (weak).

An ANOVA identified which groups were significantly different from each other with regard to summative assessment scores, $F(6, 145), = 2.75, p < 0.015$. However, Levene's test for Homogeneity of Variance ($p = 0.041$) indicated variances were not within limits for the ANOVA. Kruskal Wallis results indicated on non-statistically significant finding, H $(6) = 10.18 = p = 0.12$.

Active engagement

Active engagement variables consisted of Instructor Post Views, Student Post Views and Hyperlinks Clicked. These variables were compared to overall discussion scores. The regression model shown in Table 3 showed a moderately positive correlation which explained 48% of the variation.

Although this moderate correlation was statistically significant, only the Student Post Views variable was statistically significant. Taken by itself, the variable of Student Post Views showed a similar correlation by itself than in the model shown in Table 3. Student Post Views showed a moderate correlation with overall discussion scores, r(19) 0.686, $p < 0.001$. The coefficient of determination was 0.471 accounting for 47% of the variation.

A regression model with the active engagement variables was applied to overall summative assessment scores yielding an r squared value of 0.135 and an adjusted r squared value of -0.027, ($p = 0.496$). Active engagement variables appeared to be a poor predictor of summative assessment scores.

Passive engagement

Factors measured were badges received, number of replies received on students' initial post, and up votes received. The regression model (Table 4) showed a moderate correlation between these three variables and discussion scores students earned. The relationship between Badges Received, Replies Received on Initial Posts, Up-Votes Received, and discussion scores is depicted in Figure 8. The regression model accounted for 54% of the variation between the variables.

This trend, however, did not translate to summative assessment scores. The identical predictor variables showed a very week correlation with summative assessment scores. Up-votes Received was the only passive engagement predictor variable that had a significant correlation. Taken by itself, Up-votes Received had a weak association with summative assessment scores, r(178) = 0.25, $p < 0.001$, accounting for only 6% of the variation.

The results support the idea of a relationship between higher number of Badges Awarded by instructors, Up-votes Received and higher discussion scores. The data also yielded a weak but significant relationship between number of Up-votes Received and summative assignment scores.

RQ2: Categorization of Learner Engagement into Profiles

Table 3. Multiple regression: active engagement and discussion scores

Variable	Estimate	Standard error	DF	*T*-stat	*p* value
Student post views (#)	0.889	0.235	16	3.783	0.002
Hyperlinks clicked (#)	−1.710	2.656	16	−0.644	0.529
Instructor post views (#)	0.891	5.464	16	0.163	0.873

Source	DF	SS	MS	*F*-stat	*p*-value
Model	3	7372.50	2457.50	5.019	0.012
Error	16	7833.90	489.62		
Total	19	15206.40			

Note(s): Summary of fit:
Root MSE: 22.127
R-squared: 0.485
R-squared (adjusted): 0.388
Source(s): Table by authors

Table 4. Multiple regression passive engagement factors and discussion scores

Variable	Estimate	Standard error	DF	*T*-stat	*p* value
Badges received	21.329	2.420	176	8.814	<0.001
Replies received on IPs	11.718	3.113	176	3.765	0.002
Up-votes received (#)	10.838	5.053	176	2.145	0.033

Source	DF	SS	MS	*F*-stat	*p*-value
Model	3	1177307.30	392435.780	71.631	<0.001
Error	176	964231.87	5478.590		
Total	179	2141539.20			

Note(s): Summary of fit:
Root MSE: 74.017
R-squared: 0.550
R-squared (adjusted): 0.542
Source(s): Table by authors

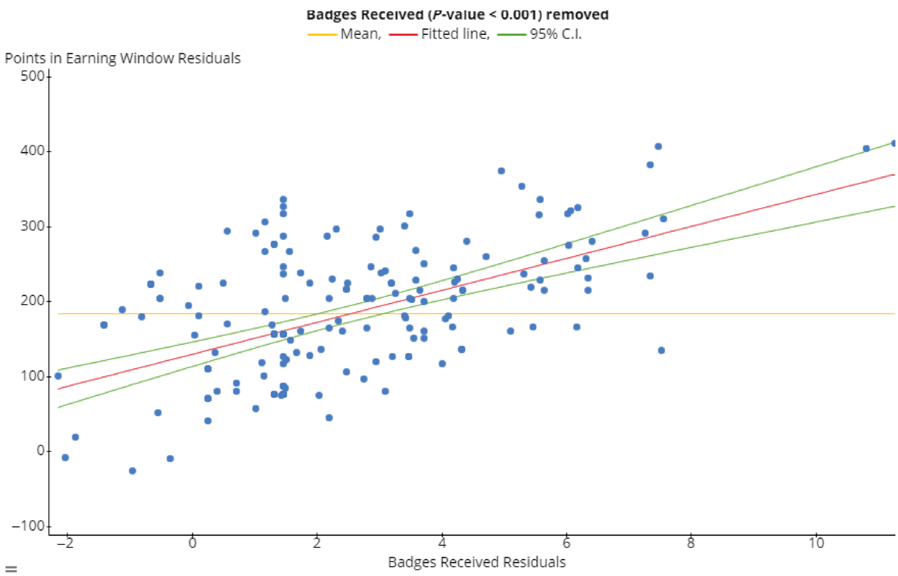

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Figure 8. Passive engagement variables and discussion points score for earning window

The data were examined to identify possible student engagement profiles (using the ICAP framework) based on their activities in the Yellowdig discussion boards. Some possible student profiles presented themselves based on examination of the data. For each variable, student activity was compared with their peers to generate a z score for each variable. These z scores were then compiled to generate a composite activity z score for each student which allowed students to be broken into groups (Table 5).

The four engagement profile groups were analyzed with respect to activity level, discussion scores and summative assessment scores.

Table 5. Engagement profile groups

Engagement profile groups	Z score criteria
1. Significantly low activity	−2 SD below peers
2. Low activity	−2>−1 SD below peers
3. Moderately low activity	−1<0 SD compared to peers
4. Moderately high activity	0 < 1 SD above peers

Source(s): Table by authors

RQ3: Relationship between Engagement Profile and Performance

Engagement profiles were useful in showing the relationship between engagement and performance. Significantly low and Low activity groups were similar to each other and Moderately low and Moderately high activity groups were also similar to each other. However, these two groupings (1 and 2 vs 3 and 4) were significantly different (Table 6).

An Analysis of Variance (ANOVA) was conducted to determine if there was a difference in discussion scores based on engagement profile group. Groups 1 and 2 had means of 38 and 22% respectively. Groups 3 and 4 had means 98 and 96% respectively. The results, $F(3, 16), = 77.54$, $p < 0.001$, necessitated a Tukey HSD (Honestly Significant Difference) test which significant differences between the low and moderate engagement profile groups as shown in Table 6. Levene's test for Homogeneity of Variance ($p = 0.12$) indicated variances were within limits for the ANOVA. These relationships are shown in Figure 9, which shows the significant differences of the two lowest activity engagement profile groups 1 and 2 and the moderately low and moderately high activity groups 3 and 4 regarding overall (course) discussion scores. Moderately high and moderately low activity profile groups (groups 3 and 4) earned significantly higher discussion scores than groups 1 and 2 who exhibited low or significantly lower activity levels based on composite Z scores.

An ANOVA was also conducted to determine if there were differences between engagement profile groups and summative assignment scores, providing inconclusive results because of group size (Table 7).

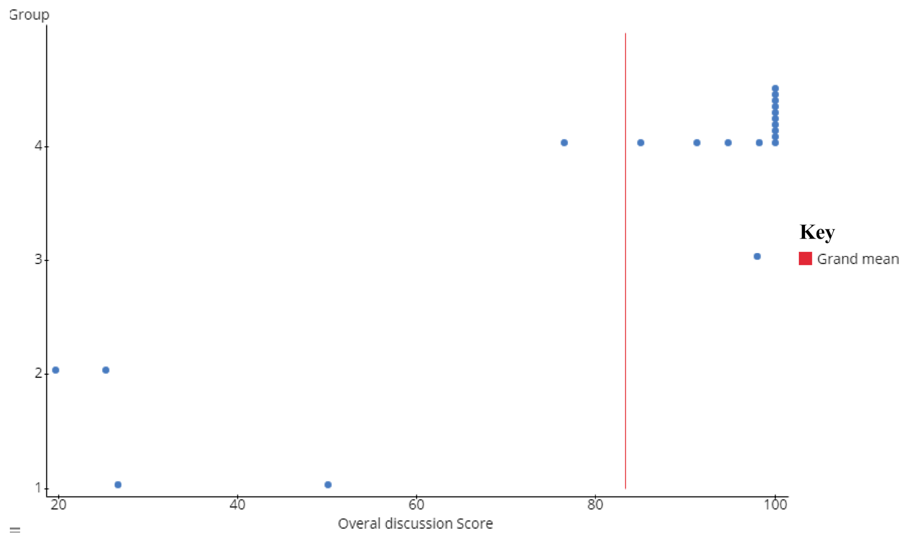
The ANOVA results, $F(3, 16), = 8.25$, $p < 0.002$, necessitated a Tukey HSD (Honestly Significant Difference) test which noted significant differences between group 3 and the remaining groups as shown in Table 5. Levene's test for Homogeneity of Variance ($p = 0.08$) indicating variances were within limits for the ANOVA. Caution should be taken in drawing any other concussion that aside from the lone student in group 3 who had a score of 54%, the remaining groups 1, 2 and 4 scored similarly with averages between 80 and 86%.

Students who were more active than their peers tended to do better in discussion scores than students who were significantly less active, though this relationship did not translate to summative assignment scores.

Table 6. Engagement profile groups determined by composite activity Z scores and overall discussion scores

Engagement profile groups	Criteria	Significantly different from
1. Significantly low activity	−2 SD below peers	Groups 3 and 4, $p < 0.001$*
2. Low activity	−2>−1 SD below peers	Groups 3 and 4, $p < 0.001$*
3. Moderately low activity	−1<0 SD compared to peers	Groups 1 and 2, $p < 0.001$*
4. Moderately high activity	0 < 1 SD above peers	Groups 1 and 2, $p < 0.001$*

Source(s): Table by authors



Source(s): Figure by authors

Figure 9. Dotplot of engagement profile group and overall discussion scores

Table 7. Engagement profile groups determined by composite activity Z scores and overall summative assignment scores

Engagement profile groups	Criteria	Significantly different from
1. Significantly low activity	−2 SD below peers	Group 3, $p = 0.002$*
2. Low activity	−2>−1 SD below peers	Group 3, $p = 0.01$*
3. Moderately low activity	−1<0 SD compared to peers	Group 1, 2 and 4
4. Moderately high activity	0 < 1 SD above peers	Group 3, $p = 0.01$*

Source(s): Table by authors

Conclusion

The findings from this study highlight factors influencing student performance in asynchronous online discussions in Yellowdig, including actions that are directly points-bearing and those that are not. Engagement profiles were created using the ICAP framework and were correlated to outcomes.

Engagement behaviors

Interactive engagement. Several behaviors categorized as interactive engagement significantly correlated with higher discussion scores. A multiple regression model revealed the impact of quick and frequent reply posts on discussion scores. Each reply post earns the student who made the reply points. Earlier student replies during the week had a positive influence on discussion scores. Making reply posts earlier in the module allows a longer window of opportunity for those in the learning community to up-vote the reply post and for the instructor to assign an accolade as a badge for the reply post.

Constructive engagement. Learners who made their initial post early in the week scored higher on the discussions than those who did not. Specifically, those who made their initial post less than three days prior to the deadline scored worse than those who initially posted three days or more before the deadline. In cases where initial posts were made earlier, the learning community had a longer period to react to and interact with the post, which earns points for the student who made the post. However, this positive relationship did not extend to summative assessment scores, which suggests a limited influence of constructive engagement in the discussion on content mastery. There was not enough evidence to support the idea that those who made an initial post (a constructive engagement behavior) later in the module made fewer reply posts overall in the module (an interactive engagement behavior).

Active engagement. Active engagement variables showed a moderate correlation with discussion scores. However, only one of the three variables, Student Post Views, was significantly correlated to discussion scores. In this study, the moderate correlation of Student Post Views was just as effective as the combination all three active engagement variables with regard to correlation with discussion scores. Active engagement variables were weakly correlated with summative assessment scores. Although the lone variable of Student Post Views was moderately correlated with discussion scores, it was not a good predictor of summative assessment scores.

Passive engagement. Badges Received, Up-Votes Received, and Replies Received were all positively correlated to discussion score performance. Earning badges, up-votes, and replies are all points-incentivized in Yellowdig. However, passive engagement variables showed very weak correlation with summative assessment scores.

Engagement profiles

Engagement profiles were useful in distinguishing low versus moderate activity groups with regard to discussion scores. Students identified in the low engagement groups earned lower discussion scores than students in the moderate engagement groups. The argument that engagement profiles can be used to predict performance was supported by the findings in this study.

Implications for practice. This research supports findings by Kovanović *et al.* (2015) regarding the identification of engagement profiles and possible use of those profiles to predict student performance and inform teaching methodology.

Yellowdig is designed to foster more student interaction by using social media like tools such as badges and emoticons. Grading can be designed to allow students to post on past topics and even miss a week, (making up the points in another module), without hurting their grade. In this study Yellowdig facilitated student engagement and provided statistical data that was used to assess that engagement. It should be noted that other options besides Yellowdig might have different results.

Although this research gave excellent insight as to student behaviors and was able to identify four learner profiles, replication with a larger sample size might uncover more associations between student behavior and performance. Student engagement profiles should be used in further research regarding student behavior and performance. Students should be encouraged to post early in the points earning window (e.g. week or module).

Limitations and next steps. This study was conducted at a mid-sized university with nontraditional students (average age 34, 76% male, mostly military affiliated) who took a 9-week online course. Care should be taken in generalizing these results to other contexts. This research evaluated Yellowdig as a discussion enhancement tool. Use of other discussion platforms might have different results.

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