

# Planning for Success: How Students Use a Grade Prediction Tool to Win Their Classes

Caitlin Holman<sup>1</sup>, Stephen J. Aguilar<sup>2</sup>, Adam Levick<sup>1</sup>, Jeff Stern<sup>1</sup>,  
Benjamin Plummer<sup>2</sup>, Barry Fishman<sup>1,2</sup>

<sup>1</sup>University of Michigan  
School of Information & USE Lab  
105 S. State Street,  
Ann Arbor, MI 48109-1285 USA  
+ 1(734) 647-8027

<sup>2</sup>University of Michigan  
School of Education & USE Lab  
610 E. University Ave  
Ann Arbor, MI 48109-1259 USA  
+1 (734) 764-8416

cholma@umich.edu, aguilar@umich.edu, adlev@umich.edu, jeffster@umich.edu,  
bdplum@umich.edu, fishman@umich.edu

## ABSTRACT

Gameful course designs require a significant shift in approach for both students and instructors. Transforming a standard course into a good game involves fundamentally altering how the course functions, most notably by giving students greater control over their work. We have developed an application, GradeCraft, to support this shift in pedagogy. A key feature of the application is the Grade Predictor, where students can explore coursework options and plan pathways to success. We observed students in two gameful courses with differing designs using the Grade Predictor in similar ways: they spent similar amounts of time per session, increased usage when assignments were due and before making significant course decisions, predicted different types of assignments at different rates, and made more predictions in preparation for the end of semester. This study describes how students plan their coursework using the GradeCraft Grade Predictor tool.

## Categories and Subject Descriptors

K.3.1 [Computers and Education]: Computer Uses in Education – *computer-assisted instruction, computer-managed instruction.*

## General Terms

Management, Measurement, Design, Human Factors, Theory

## Keywords

Learning Analytics, Design-Research, Gameful Instruction, Higher Education

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from [Permissions@acm.org](mailto:Permissions@acm.org).

LAK'15, March 16–20, 2015, Poughkeepsie, NY, USA. Copyright is held by the owner/author(s). Publication rights licensed to ACM.  
ACM 978-1-4503-3417-4/15/03...\$15.00  
<http://dx.doi.org/10.1145/2723576.2723632>

## 1. INTRODUCTION

Gameful instruction uses the design of successful games as inspiration for the *redesign* of formal courses [8, 9, 14]. A central goal of this approach is to increase student engagement and motivation, enabling students to take on a more active role in their own education [3, 7]. Common mechanics employed by gameful classrooms include: having students begin with zero points and earn them by completing assignments [7]; promoting student autonomy by offering a variety of assignments to students and allowing them to select which ones to complete [8]; implementing leveling systems; using avatars and pseudonyms to experiment with identity within the course [15]; awarding badges to recognize excellence [3]; and providing multiple pathways for students to practice new skills—and recover in the event of failure [1].

Implementing gameful course designs has proven to be challenging for both instructional staff and students. Typical learning management systems (LMS) are designed to support course structures where assignment grades are weighted according to a pre-determined scheme to calculate a student's final grade. This makes it difficult, if not impossible, to accurately track student progress through the individualized and additive pathway structure that gameful courses afford.

Past research indicates that even when multiple pathways to success in a class exist, they may be difficult for students to visualize [7]. In an effort to support students' awareness of their choices in gameful course environments, we designed and developed GradeCraft, an online tool intended for use in conjunction with a primary LMS like Sakai or Canvas. GradeCraft helps students explore gameful syllabi and plan unique pathways to success, while making it possible for instructors to manage the workflow of these personalized course structures [10].

In this paper we explore how GradeCraft was used in two different gameful courses, employing event data, grade outcomes, and survey responses to examine how the Grade Predictor helped students to strategize their coursework and related to learning and motivation outcomes.

## 2. BACKGROUND

Gameful course designs are in the early stages of development; there is much still to be learned regarding which aspects reliably support student motivation and learning, and under what

conditions elements function most effectively. In a multi-year study, comparing student engagement and outcomes in a gameful course design as compared to the same course run in a traditional format, resource access and discussion forum posts increased in the gameful course implementations, but student grades and lecture attendance did not [3]. Outside of the classroom, research is also underway to understand the effects of specific game mechanics: Mekler, et al., showed that the use of points, levels, and leaderboards could successfully boost performance during an image annotation task, but that these mechanics had no effect on participants' intrinsic motivation [11]. The effects of surface-level gamification is mixed in terms of its effect on motivation and performance. The implementation of gameful elements as a foundation for course structure need further investigation to see if they are more consistently motivating than surface integration.

Self-determination theory (SDT) is a useful theoretical framework when thinking about the design of gameful courses. It posits that support for three core human needs – autonomy, belonging, and competence – is essential to producing intrinsic motivation. Intrinsic motivation in learning has been linked to greater conceptual learning and increased future interest in the topic or skill [6][5][4]. *Autonomy* in the classroom is commonly interpreted as empowering students' ability to make meaningful decisions regarding how and what they will learn, and in what form they will be assessed. *Competence* highlights to the need to challenge learners at the upper edge of their current skill level, where they have an equal chance of success or failure. *Relatedness* refers to the need to support connections between peers, as well as between individual students and their instructors. Part of the appeal of video games as inspiration for course design is the ease at which some seem to have successfully satisfied these needs for players. However, because games often maintain a layer of behavioral incentives to drive player action, there has been concern regarding the type of motivation they produce, and whether it is appropriate for application to educational settings. Ryan, Rigby, and Pryzbylski's study on player motivation in video games indicates that in-game support for each of the three needs of SDT produced greater well-being in players (as expected when intrinsically motivated), and increased the likelihood of their playing the game in the future [13]. This suggests that supporting the SDT framework within the design of gameful courses is worthy of effort and investigation provided that students are able to make sense of the choices available to them.

### 3. GRADECRAFT

GradeCraft is a web application developed at the University of Michigan (UM) and dedicated to supporting gameful instruction. At the time of this study, GradeCraft's features included: a grade planning utility we call the "Grade Predictor," badges, teams and team challenges, individualized assignment values where students set the degree to which assignments will count towards their grade, leveling displays, and opt-in pseudonym-driven leaderboards.

GradeCraft is built using Ruby on Rails, and deployed on Amazon Web Services (AWS) Elastic Compute Cloud (EC2). Feature development occurs in response to feedback from faculty and students, and our own evolving understanding of how design interacts with student motivation. This paper focuses on student use of the Grade Predictor.

#### 3.1.1 The Grade Predictor

The Grade Predictor (Figure 1) was designed to support student autonomy in gameful courses by helping them visualize the possibly ways they could choose complete the assignment work for the course successfully. The tool enables students to actively experiment with which assignments they will work on, predict how they will perform, and visualize the course grade they will earn as a result. As the semester progresses, the Grade Predictor fills in with students' actual grades, keeping them informed of their progress towards achieving their desired grade.

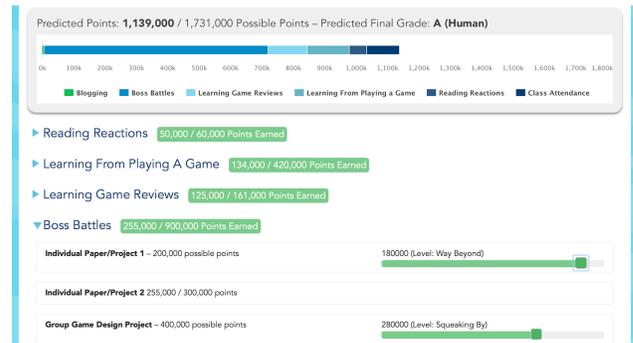


Figure 1: The GradeCraft Grade Predictor

### 3.2 Research Questions

This paper addresses the following research questions:

- (RQ1) How do course events relate to Grade Predictor activity?
- (RQ2) At what rate do students follow through on completing the coursework they predict?
- (RQ3) How do grade prediction behaviors differ between courses?

## 4. METHODS

### 4.1 Setting and Implementation

The following sections describe the pedagogical design of the two gameful courses, *Intro to Political Theory* and *Intro to Information Studies*, which are the settings for our analysis.

#### 4.1.1 Intro to Political Theory

The grading system in *Intro to Political Theory* was designed to support students' autonomy through a two-step process. First, students selected two out of four assignment types to complete: in-class exams, essays, blogging, or a group project. Second, students determined how these types were counted towards their grade (lecture attendance, reading quizzes, and participation in a discussion section also counted, but were not weighted).

#### 4.1.2 Intro to Information Studies

*Intro to Information Studies* also incorporated two elements aimed at supporting student autonomy and belonging. First, a variety of assignment pathways were available so that students could direct their course experience. Second, students were organized into "houses" and collectively earned points for achievement on house challenges throughout the semester.

### 4.2 Participants

There were 292 students enrolled in *Intro to Political Theory*, and 231 students in *Intro to Information Studies*, both large lecture classes that act as gateways for their respective majors. Table 1 shows the demographic and academic information about the class participants as obtained from UM's central student database.

**Table 1: Participants' Demographics and Year in School**

	<i>Intro to Political Theory</i> (N=292)	<i>Intro to Information Studies</i> (N=231)
<i>Gender</i>		
Female	41.90%	43.90%
Male	58.10%	56.10%
<i>Ethnicity</i>		
Caucasian	69.37%	65.85%
African American	3.52%	3.90%
Hispanic	3.87%	4.39%
Asian	13.38%	18.54%
Other	1.76%	0.98%
<i>Academic Year</i>		
Freshmen	49.30%	50.73%
Sophomores	36.97%	15.12%
Juniors	9.15%	21.95%
Seniors	4.58%	12.20%

## 4.3 Data Sources

### 4.3.1 Data Processing and Reduction Procedures

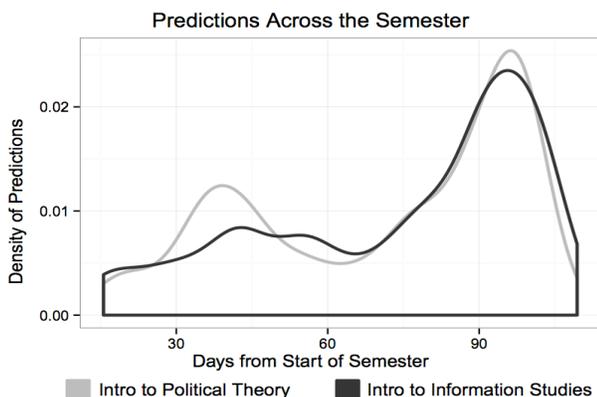
GradeCraft uses the Granalytics [2] open source Ruby on Rails gem to record platform-use analytics. Events were logged via Redis and stored in a MongoDB NoSQL database. Grade data and analytics data were merged and prepared for analysis using Python and the pandas library [12]. We used Python to calculate the total number of predictions made for each assignment by each student. Because the event logging recorded all intermediate predicted values, we only included predictions in this calculation if they occurred more than three seconds after the previous prediction for the same assignment by the same student.

## 5. RESULTS

There were a total of 4,763 predictor sessions throughout the semester. 90% of students in *Intro to Information Studies* made predictions (with an average of 9 sessions per student), as compared to 95% of *Intro to Political Theory* students (on average 10 sessions per student). Students in both courses used the Grade Predictor at similar times throughout the term, and the sessions in both courses were roughly equal in length.

### 5.1 Grade Predictor Use by Session

Data indicate that predictor sessions were generally short, with over 43% of them taking less than thirty seconds, and 74% of the remainder finishing within three minutes (Figure 2).



**Figure 2: Days from Start of Semester Compared to Density of Predictions**

### 5.1.1 RQ1: Grade Predictor Use Through the Term

In answer to RQ1, we can see the majority of predictions occurred during two major peaks, which correspond with midterms and finals (Figure 2). Heat map analysis (Figures 3 and 4) shows an increase in use at both the middle and end of the term, and a dip in activity on the weekends. By marking the due dates of large assignments in each course using a solid black vertical line, we then often see an increase in grade prediction activity on the day these assignments are due (represented by the block immediately to the right of the line). We also see an increase in sessions between midnight and 3AM during midterms and finals.

*Intro to Political Theory* also shows a block of high activity between weeks 6 and 8. The end of this time period coincides with when students had to decide how to weight their assignments to determine their final grade, suggesting that they used the Grade Predictor to inform their choice.

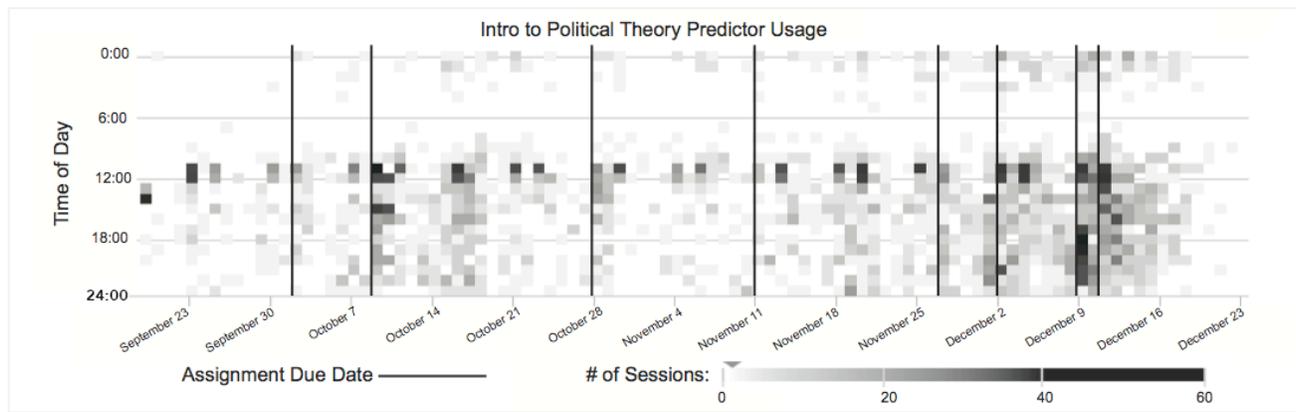
## 5.2 Grade Predictor Use by Assignment Type

Tables 3 and 4 summarize students' prediction behaviors categorized by assignment type. The *Predicted* column shows the percentage of students in the whole class who used the Grade Predictor to estimate their performance for assignments within each category; *Graded* refers to the percentage of students who completed these assignments (many of whom did so without predicting their performance); *Grade Only* shows the percentage of students who earned a grade but never made a prediction; and *Predictor Follow-Through* show the percentage of students who made a prediction and then followed through on that plan, as observed by their having a grade (RQ2).

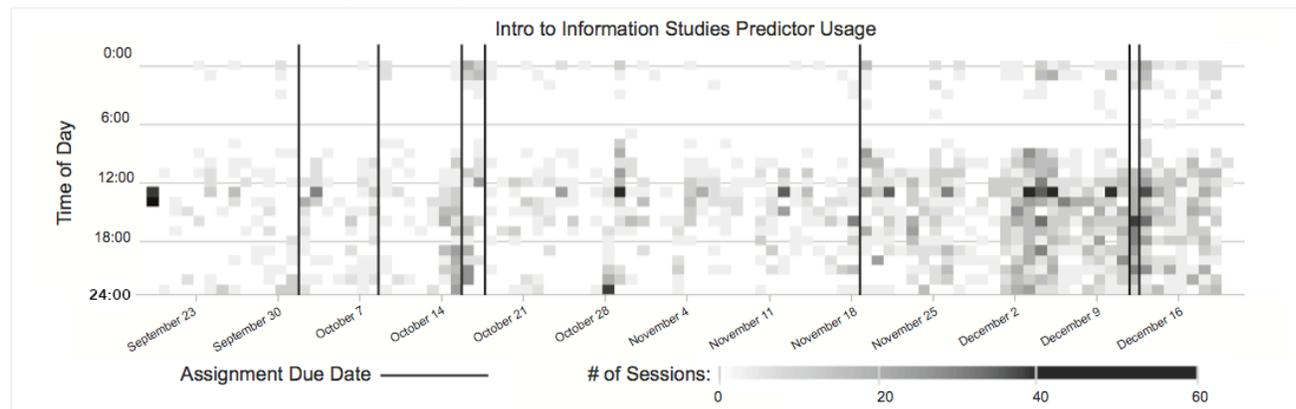
**Table 3. *Intro to Political Theory*: Percentage of total class who made a prediction, percentage of total class who received a grade, percentage of students who received a grade but never made a prediction, and percentage of students who made a prediction and then earned a grade** \*= Optional assignment category

	<i>Predicted</i>	<i>Graded</i>	<i>Grade Only</i>	<i>Predictor Follow-Through</i>
*Essays	61%	81%	30%	93%
Attendance	54%	96%	46%	96%
Discussions	54%	96%	48%	93%
Readings	54%	94%	45%	95%
*Exams	51%	63%	38%	75%
*Blogging	36%	42%	48%	60%
*Group Projects	36%	31%	23%	65%

Across all but one assignment type, fewer students in *Intro to Political Theory* predicted grades than earned them. Approximately 54% of the class predicted their grades for the weekly activities of Attendance, Readings, and Discussion Sections, and 93%-96% of those who made a prediction for these assignments followed through on those plans (*Predictor Follow-Through*). Essays stand out as the single most predicted category, and maintain a 19%-34% higher follow-through rate as compared to the other optional assignment types of Exams, Blogging, and Group Projects. We know from the instructor that he heavily encouraged all students to try this assignment (but did not require it), which may explain the increased activity around this work as compared to the other optional elements. Blogging and Group Projects were both predicted at the same rate, with approximately



**Figure 3: Heat map showing prediction sessions in Intro to Political Theory across the semester**



**Figure 4: Heat map showing prediction sessions in Intro to Information Studies across the semester**

one third of the class considering these options. Group Projects represents the one place where fewer students predicted their grades than earned grades – this assignment type required students to submit a proposal for approval, so it makes sense that some students might have planned to engage in this activity by had their proposal rejected. Comparatively, Blogging as an assignment type displays the highest (alongside Discussions) rate of students who earned a grade but never made a prediction. This could reflect that students perceived this category to be easier thus making it less important to predict.

**Table 4. Intro to Information Studies: Percentage of total class who made a prediction, percentage of total class who received a grade, percentage of students who received a grade but never made a prediction, and percentage of students who made a prediction and then earned a grade \* = Optional assignment category**

	Predicted	Graded	Grade Only	Predictor Follow-through
Boss Quests	80%	99%	19%	100%
Newbie Quests	66%	98%	35%	97%
Adventures	49%	88%	44%	99%
*Mighty Tomes	43%	27%	33%	41%
*Random Encounters	37%	42%	57%	48%
*Side Quests	28%	35%	74%	34%
*Explorer Reports	19%	13%	69%	23%
*Pick Up Quests	11%	34%	88%	36%

Similarly to *Intro to Political Theory*, more students earned grades than made predictions in all but two assignment categories (Mighty Tomes and Explorer Reports). The most predicted assignment category for this class was Boss Quests, where all students were expected to complete one of the three assignments; 80% of students made a prediction for their achievement, while 99% of the total class completed the work. Newbie Quests and Adventures were also compulsory, and showed a similar pattern to the required assignments in *Intro to Political Theory*—approximately half of the class made predictions, and those who did had a near-perfect completion rate. However, whereas in *Intro to Political Theory* students were asked to make a distinct choice at a specified date, in *Intro to Information Studies* students were free to do any of the optional assignments throughout the semester. Less than half of the class earned grades for any single optional category, suggesting that students were able to customize the class to their own interests and abilities, and the low prediction rates indicate that they did not require the Grade Predictor’s support to be able to achieve success.

In each class students appear to have used relatively standard (required) assignment categories as a foundation on which they then planned which of the optional components to complete. This would explain why we see relatively higher patterns of predicting attendance assignments as compared to blog posts or group projects in *Intro to Political Theory*. Since there were more optional assignments within certain categories (e.g. side quests) and assignments options were not as effectively portrayed in *Intro to Information Studies*, we observed lower engagement overall compared to *Intro to Political Theory* (RQ3).

## 6. Limitations & Future Work

This study was limited by a gap in log file data for the first two weeks of the semester when students might have been using the Grade Predictor. In future work, we will be able to get a more comprehensive picture of students' grade predictions by recording their engagement with the tool from the beginning of the semester. Furthermore, the event tracking data do not allow us to distinguish between times when students were merely "playing" with the Grade Predictor as opposed to actively engaged with predicting their grades. We need to do more to categorize the different types of predictor sessions students engage in, and determine what, if any, analytic markers we can use to distinguish them. We also intend to explore how the value of students' grade predictions relates to the scores they receive on individual assignments, and to their overall course success.

## 7. Conclusion

In answer to RQ1, there was a clear increase in grade prediction leading up to the traditional high-intensity moments of midterms and finals, at the choice point in a class that required students to make a strategy in the semester (the due date for assignment weighting decisions in *Intro to Political Theory*), and in response to assignment due dates. Both the type of assignment (smaller, weekly assignments versus larger, periodic work), and the context of assignment selection structure seem to have affected whether students followed through on their predictions (RQ2).

Outside of the structural relationships we saw, these courses differed greatly in how much follow-through students displayed (RQ3). In *Intro to Political Theory*, the smaller number of assignments may have made it easier for students to predict more accurately than in *Intro to Information*. Alternatively, grade prediction may have been less necessary for students to feel like they were in control of their own success in *Intro to Information*.

This study represents a first step in assessing how students use the GradeCraft Grade Predictor to plan their work over the course of the semester. Both of the courses studied are themselves works in progress, changing in scope each semester. Now that we have established a baseline understanding of how students use the Grade Predictor tool we look forward to being able to explore how structural changes impact student planning and engagement.

A common refrain we hear from students after they use the Grade Predictor has been, "I wish I had this for all of my courses!" While we believe that this type of planning tool is especially important to support courses where central elements rely on student-driven choice, we hope that this work will inspire additional dialogue beyond just the gameful learning community around how to provide students with opportunities and tools that empower them to take control of their own learning outcomes.

## 8. Acknowledgements

Our thanks to the University of Michigan USE Lab, the Office of Digital Education and Innovation, the Learning Analytics Task Force, Stephanie Teasley, Steve Lonn, Mika LaVaque-Manty, Cliff Lampe, Tim McKay, and all of the students who have helped us design and build GradeCraft.

## 9. REFERENCES

- [1] Aguilar, S., Holman, C. and Fishman, B. Multiple Paths, Same Goal: Exploring the Motivational Pathways of Two Distinct Game-Inspired University Course Designs. (Madison, WI).
- [2] AlfaJango 2014. *Granalytics*.
- [3] Barata, G., Gama, S., Jorge, J. and Gonçalves, D. 2013. Improving Participation and Learning with Gamification. *Proceedings of the First International Conference on Gameful Design, Research, and Applications* (New York, NY, USA, 2013), 10–17.
- [4] Black, A.E. and Deci, E.L. 2000. The effects of instructors' autonomy support and students' autonomous motivation on learning organic chemistry: A self-determination theory perspective. *Science Education*. 84, 6 (Nov. 2000), 740–756.
- [5] Deci, E.L. and Ryan, R.M. 2002. *Handbook of self-determination research*. University of Rochester Press.
- [6] Deci, E.L. and Ryan, R.M. 1985. *Intrinsic motivation and self-determination in human behavior*. Plenum.
- [7] Fishman, B.J. and Aguilar, S. 2012. Gaming the Class: Using a Game-based Grading System to Get Students to Work Harder... and Like It. *Proc. GLS 8.0* (2012), 111–118.
- [8] Fishman, B.J., Deterding, S., Vattel, L., Higgen, T., Schenke, K., Sheldon, L., Ewing, C., Holman, C. and Aguilar, S. Beyond Badges & Points: Gameful Assessment Systems for Engagement in Formal Education. *Games + Learning + Society* (Madison).
- [9] Gee, J.P. 2003. *What videogames have to teach us about learning and literacy*. Palgrave Macmillan.
- [10] Holman, C., Aguilar, S. and Fishman, B. 2013. GradeCraft: What Can We Learn from a Game-inspired Learning Management System? *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (New York, NY, USA, 2013), 260–264.
- [11] Mekler, E.D., Brühlmann, F., Opwis, K. and Tuch, A.N. 2013. Do Points, Levels and Leaderboards Harm Intrinsic Motivation?: An Empirical Analysis of Common Gamification Elements. *Proceedings of the First International Conference on Gameful Design, Research, and Applications* (New York, NY, USA, 2013), 66–73.
- [12] pydata 2014. *pandas*.
- [13] Ryan, R.M., Rigby, C.S. and Przybylski, A. 2006. The Motivational Pull of Video Games: A Self-Determination Theory Approach. *Motivation and Emotion*. 30, 4 (Dec. 2006), 344–360.
- [14] Sheldon, L. 2012. *The multiplayer classroom: Designing coursework as a game*. Cengage Learning.
- [15] De Shutter, B. and Abeele, V.V. Gradequest - Evaluating the impact of using game design techniques in an undergraduate course.