Transparency and Engagement in Online Course Design: Analysis of Effectiveness and Student Perception

Introduction

The Bologna process ensured that quality education and student satisfaction are important topics in Europe (Bassi, 2018). Students expect a higher level of education and educators are looking for new and better ways of ensuring it. This can be challenging in a virtual learning environment as nonverbal feedback is missing. Accordingly, instructors in virtual settings need to take extra steps to create effective interactions with and among students. This case study was designed to review class activities, tools, and processes aimed at accomplishing greater transparency and supporting goal achievement. The goal of this explorative study is to understand if and to what extent formative assessments, in the form of interactions dispersed throughout webinars, impact student engagement and achievement of the desired learning outcomes as ascertained by the summative assessments.

Background

As instructors at all levels of education share the common goal of wanting to deliver quality education, a major focus of the study of didactics is on how to teach effectively (UNESCO, 2016). Two of the main methods for evaluating effectiveness in teaching and student learning are formative and summative assessments (Parker, 2013). While Summative Assessments (SA) are heavily based on exams, papers, and presentations, formative assessment (FA) focuses on in-class questions, discussions, and other interactions. SA allows educators to assess student achievement of desired learning outcomes after the student has completed the work. Conversely, FA enables educators to monitor student progress and adjust instructional content and delivery throughout the course (Gikandi et al., 2011).

The question then becomes how we can use FA and SA in combination with data on student interaction to be more effective. To assess program effectiveness, corporate training and development departments often utilize the Kirkpatrick program evaluation model (Kirkpatrick, 1967), a model also applicable in higher education (Praslova, 2010). It offers four steps for course evaluation in the university context: reaction (students' satisfaction), learning (SA), behavior (students apply learning to future courses) and results (success as alumni). While reaction and learning can be assessed during one course, future behavior and results cannot be foretold.

To examine course effectiveness, many educators are turning to learning analytics (LA) (Wong et al., 2018). LA "is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Winne, 2017, p. 241). Usually utilized with big data; a lot of value can still be gained starting with less (Broos et al., 2017).

Methodology

We conducted this exploratory study with 23 Bachelor students of a university of applied sciences in Austria. The blended learning study program combines six synchronous online sessions (webinars), one synchronous on-campus day, and asynchronous independent learning per course.

FA, ongoing student feedback, transparent design decisions, and LA were implemented in one particular course. Data collection focused on FAs in the virtual classroom, weekly surveys, and SAs. The institution's learning management system was excluded as an option for data collection due to system limitations.

The course took place October through November 2019 with weekly webinars on Tuesdays from 8.00-10.00 p.m. Webinars took place in a dedicated Adobe Connect room. At that time, all participants were employed and attended webinars in the evenings after work. The late hour of the class made keeping students engaged an added challenge.

To counter this challenge, the instructor utilized frequent interactions. The interactions were designed with two objectives in mind. First, to keep students engaged. The interactions were placed five to ten minutes apart from one another throughout a webinar to keep students from losing focus. Secondly, interactions were used to get a sense of students' mastery of the content.

Adobe Connect and Google forms enabled different interactions, including multiple-choice and short answer polls, word clouds, and breakout sessions. Accordingly, students did not need to leave the Adobe environment to participate. Data on poll interaction was gathered throughout the duration of the course, focusing on participation instead of correctness.

Focusing on level one (reaction) of the Kirkpatrick model (1967), weekly surveys (Table 1) via Google forms were launched through Adobe Connect to students' screens at the end of each class.

Question	Response Option
The class speed was …	Five-point scale: too slow (1) - too fast (5)
The content was …	Five-point scale: unclear (1) - very clear (5)
What did you like?	Short answer
What could be better?	Short answer

Table 1: Questions asked after each webinar.

In addition to addressing course design issues as they arose, data was collected to analyze the effectiveness of the FAs (polls) compared to SAs or level two of the Kirkpatrick model (learning).

Due to the exploratory nature of this study, data collection was limited to 23 students. Consequently, SmartPLS was used to conduct Partial Least Squared Structural Equation Modeling (PLS SEM) as this type of data analysis can handle smaller sample sizes (Hair et al., 2011).

Analysis & Discussion

During the six weeks of webinars, the weekly survey results were utilized to make necessary changes to the class speed and content. Figure 1 shows the weekly feedback received for the first question regarding the speed of class. Following student feedback after the first week, the pace of the class was slowed and closely in the following weeks.

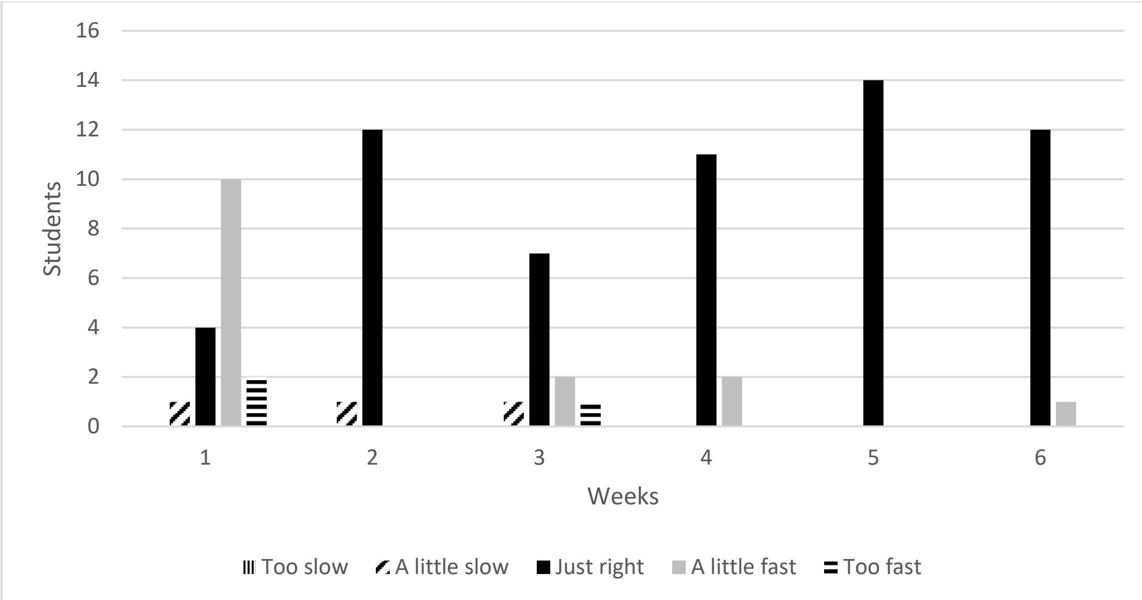

Figure 1. Student responses regarding the speed of the course content delivery.

Similar to the steps taken when reviewing student perception of the class pace, steps were also taken to adjust the content. After the first week, regular reviews of content and more FAs were incorporated to help students. This process was continued each week and content was adjusted to support student understanding.

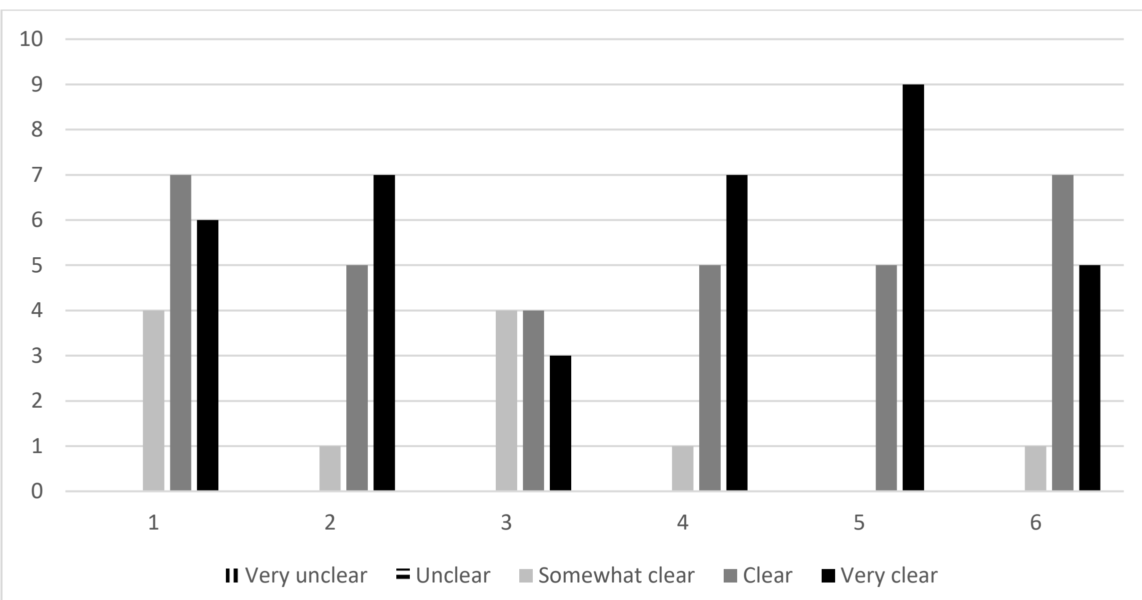

Figure 2. Student responses regarding the clarity of the course content.

The instructor reviewed the qualitative comments weekly to gain a deeper understanding of the students' needs. For the third question, "what did you like", the students emphasized that they appreciated the level of interactions. Figure 3 shows a consolidated view of the feedback.

Figure 3. Word cloud representing what students liked about the course design.

Finally, regarding the question "what could be better", students elaborated on their reasons for perceiving the pace of class as too fast, expressed their wishes for better time-management, and commented on classmates' behavior. In all cases, these comments were summarized and discussed with the class during the next session.

As previously mentioned, further analysis was conducted to understand the effect of students' participation in FAs on their SAs. Student GPA (excluding results from this class) was analyzed to understand if the *Overall Grade* (OG) is influenced more by participation or academic standing. The students' participation each week formed the variable *Participation* (Figure 4). It is important to note that the level of participation each week did not contribute equally to the variable *Participation*. Good indicators have outer loadings of at least 0.700. Specifically *Week 5*, with a loading of 0.235, is not a good indicator of the variable *Participation*. Aside from Average Variance Explained, this did not impact other quality criteria. Although *Week 5* was kept for this analysis, it is a strong indication that this lecture design needs to be reviewed critically.

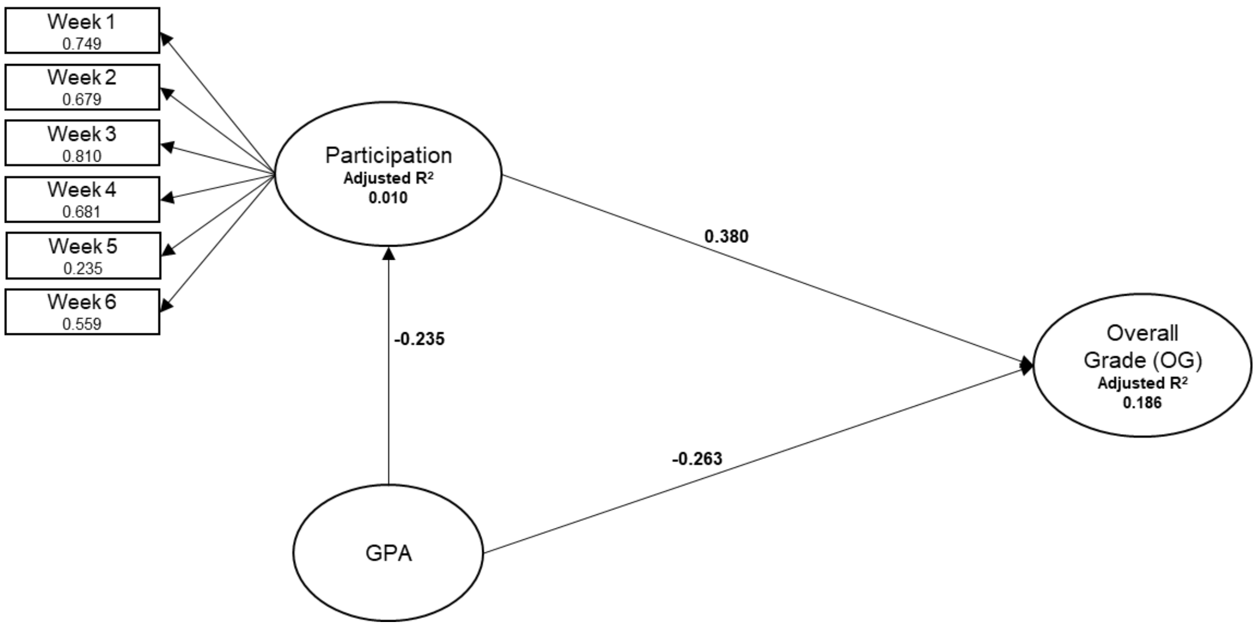

Figure 4. PLS SEM results

The results indicate that *Participation* did have a positive impact on *Overall Grade*. This is indicated by the positive path coefficient of 0.360. The students' overall GPA also had an impact on their overall course grade. The negative path coefficient of -0.263 indicates that the closer the *GPA* was to 1, the higher the *OG*. Neither of these were at a level that could be considered significant. As previously mentioned, the lack of adequate sample size could have played a large role in this result (Goodhue et al., 2006).

According to the adjusted R^2, *Participation* and *GPA* can account for 18% of the variance in *OG*. The f^2 Effect size of each predictor variable indicates how much it contributes to the R^2 of the dependent variable. Values greater than 0.02, 0.15, and 0.35 indicate small, medium and large effects respectively (Hair et al., 2013, p. 176). *Participation* has a medium (f^2 of 0.184), while *GPA* has a small (f^2 of 0.088) effect on the R^2 of OG. This shows the importance of *Participation* for student achievement. "Good" students will generally remain good students, but potentially through ongoing FAs, all students can yield better results.

Finally, the relationship between *GPA* and *Participation* was analyzed. The negative path coefficient reveals that better students (GPA closer to 1) generally participate more in class. This was not significant. The R^2 adjusted indicates that GPA only explains 1% of the variance in *Participation*.

As mentioned, PLS SEM has limitations and cannot compensate for the lack of generalizability inherent in a small sample size. Consequently, the results of this study need to be considered carefully and taken for what they are: exploratory.

Conclusion

This case attempted to understand how interactions in webinars could be effectively utilized to keep students engaged and offer FA to support student achievement of the desired learning outcomes. It also attempted to analyze the impact these FAs had on the desired learning outcome as measured by the SA. Notwithstanding the limitations, this case offers indications that structured interactions placed throughout a virtual lecture can support student achievement. Moreover, the study recognized students' appreciation for increased interactivity in webinars and thus proves the importance of expanding this research moving forward.

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