Computers & Education 87 (2015) 204–217

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Learning at distance: Effects of interaction traces on academic achievement

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A R T I C L E I N F O

Article history:
Received 27 March 2015
Received in revised form 29 June 2015
Accepted 2 July 2015
Available online 6 July 2015

Keywords:
Interactions
Online learning
Learning analytics
Learning outcome

A B S T R A C T

Contemporary literature on online and distance education almost unequivocally argues for the importance of interactions in online learning settings. Nevertheless, the relationship between different types of interactions and learning outcomes is rather complex. Analyzing 204 offerings of 29 courses, over the period of six years, this study aimed at expanding the current understanding of the nature of this relationship. Specifically, with the use of trace data about interactions and utilizing the multilevel linear mixed modeling techniques, the study examined whether frequency and duration of student–student, student–instructor, student–system, and student–content interactions had an effect of learning outcomes, measured as final course grades. The findings show that the time spent on *student–system* interactions had a consistent and positive effect on the learning outcome, while the quantity of *student–content* interactions was negatively associated with the final course grades. The study also showed the importance of the educational level and the context of individual courses for the interaction types supported. Our findings further confirmed the potential of the use of trace data and learning analytics for studying learning and teaching in online settings. However, further research should account for various qualitative aspects of the interactions used while learning, different pedagogical/media features, as well as for the course design and delivery conditions in order to better explain the association between interaction types and the learning achievement. Finally, the results might imply the need for the development of the institutional and program-level strategies for learning and teaching that would promote effective pedagogical approaches to designing and guiding interactions in online and distance learning settings.

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1. Introduction

With the development of technology, distance and online education provides a wide spectrum of interactive learning opportunities (Bernard et al., 2009; Bouhnik & Marcus, 2006; Donnelly, 2010; Woo & Reeves, 2007). Over the past few

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http://dx.doi.org/10.1016/j.compedu.2015.07.002
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decades, interaction – as a main component of distance and online learning – has been studied by various researchers (e.g., Anderson, 2003; Arbaugh & Benbunan-Fich, 2007; Bernard et al. 2004; Wagner, 1994), commonly using Moore's (1989) framework of interactions (e.g., Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014; Anderson, 2003; Kanuka, 2011). According to those considerations, learning occurs when a student *interacts* with other students or with an environment regardless of a subject domain, instructional design or the technology used in the learning process (Tirri & Kuusisto, 2013). Many researchers consider interaction as the most important component of any learning environment (Woo & Reeves, 2007), and thus, importance of interactions in both traditional (e.g., Tirri & Kuusisto, 2013; Mehan, 1998; Johnson, 1981; Yee, 1971) and distance and online educational settings (e.g., Anderson, 2003; Bernard et al. 2009; Hirumi, 2002; Lou, Bernard, & Abrami, 2006; Moore, 1989; Muirhead & Juwah, 2005; Wagner, 1994; Woo & Reeves, 2007) have been studied for a long period of time.

Despite a prevalent understanding of the importance of interaction in online education, research literature does not recognize a unique definition of interaction. Interaction is rather defined from various perspectives, within different contexts, based on the participants involved and the level of their engagement (Bernard et al., 2009; Woo & Reeves, 2007). Wagner (1994) looks at interaction from the functional perspective, as an emerging process that involves communication in various forms. Moreover, she argues that each interaction contains at least two complementary, interrelated, events that occur between two objects. Wagner (1994) also notes that the goal of interaction is to change a student's educational behavior and to bring the student closer to the learning goal. On the other hand, Yacci (2000) defines interactivity as a loop of mutually coherent messages, that should complete the cycle (from and to the student) in order for interaction to occur. The final interaction outcome is either learning of some content or affective benefits. Yacci (2000) further argues for existence of the student-centered perspective to interactivity, which means that students will not confirm the existence of interaction unless they obtain some feedback. Yacci (2000) suggests a communication theory as a valid framework for analyzing online interactions, which includes a wide variety of variables (e.g., the count and length of messages, the type of information and the amount of time spent between two messages) that should be considered when analyzing online interaction. Further, building on the previous definitions of Yacci (2000) and Wagner (1994), Muirhead and Juwah (2005) developed a similar understanding of interaction. According to their definition, interaction represents an event (i.e., communication in any possible form) that occurs between two or more subjects (participants or objects). It might occur synchronously or asynchronously utilizing technology and providing response or feedback as an outcome. Muirhead and Juwah (2005) also recognize the need to differentiate interactions depending on the context in which they occur (e.g., proactive inquiry, reactive inquiry, proactive elaboration).

The majority of the studies that analyzed interactions in online and distance education relied on a perceived measures of interaction (Bernard et al., 2009; Borokhovski, Tamim, Bernard, Abrami, & Sokolovskaya, 2012). While being useful, those measures are not always suitable, especially given the survey fatigue that is well documented in the literature (Ben-Nun, 2008) and the availability of massive amount of trace data logged by various educational platforms (Phillips, Maor, Preston, & Cumming-Potvin, 2012). Therefore, this paper offers insights into how the methods of learning analytics (Siemens & Gašević, 2012) can be used to study effects of interaction on learning in distance and online education. Specifically, the study reported in this paper aims at investigating (i) the extent to which the trace data can be used to measure the interaction types as theorized in contemporary research in distance and online education, (ii) the effects of these measures of the interaction types on learning success; and (iii) whether the effects of interactions types differ across different courses while students are progressing toward their academic degrees (from foundational to core and elective disciplinary courses).

2. Theoretical background and research questions

2.1. Interactions in distance education

The conceptual framework developed by Moore (1989) identifies three types of interactions: i) student–content, ii) student–instructor, and iii) student–student. The student–content interaction type represents the essence of education (Moore, 1989) and identifies the relation that occurs between a student and the content that describes the subject of studying. More recently, researchers and course designers, following the social constructivistic principles, suggest that content is distributed among students and thus, their focus shifts from the student–content interaction type to the student–student interaction type (Anderson, 2003; Moallem, 2003; Woo & Reeves, 2007). The student–instructor interaction type is highly valued, expensive, and least scalable type of communication (Anderson, 2003; Moore, 1989), since it requires instructors' presence and an extensive involvement of the instructor in the course facilitation and direct instruction (Garrison, Anderson, & Archer, 1999). Yet, the development of technology enabled for replacing this type of interaction with student–content interaction type (e.g., by offering more advanced instructional designs or instructional information in different formats such as video and audio) (Anderson, 2003). Finally, the student–student interaction type represents communication between students, without direct involvement of instructors in that communication (Moore, 1989). Johnson (1981) recognizes the student–student interaction type as a crucial component of healthy, socially developed community. He also argues that interaction between peers is essential for maximizing learning outcomes. For example, Schrire (2006) showed that graduate students reach higher levels of knowledge construction and learning outcomes in student–student discussions than in instructor-centered discussions.

Hillman, Willis, and Gunawardena (1994) recognized a need to introduce the fourth type of interactions. They argue that with the development of advanced online learning environments, most of interactions – that occur between students and instructors, students and content, as well as among the students – are mediated by an underlying technology. Hillman et al. (1994) also noted that students' success is related to their proficiency with a specific learning tool, and the ability to find and post right information. Thus, they suggest that it is highly significant to understand student–interface interactions as a specific component of interaction in distance and online learning. Although Friesen and Kuskis (2013) contend that student–interface interaction should not be observed as another form of interaction, but rather as a constituent of the three types of interaction proposed by Moore (1989), recent technological advances support Hillman et al.'s (1994) view. For example, Rubin, Fernandes, Avgerinou, and Moore (2010) analyzed the effect of technological affordances on student satisfaction and engagement with an online course. Rubin and colleagues showed that the perceived level of social, cognitive, and teaching presence – as defined in the Community of Inquiry model (Garrison et al., 1999) – are predicted by perceived usefulness of the Learning Management System (LMS) used to deliver the course. Rubin et al. (2010) further argue that available technological affordances might limit or enhance availability of other three types of interactions. Finally, they showed that perceived satisfaction with the LMS, also predicts students' course satisfaction when controlled for social, cognitive, and teaching presence. Likewise, Archila (2014) found that "[i]nteraction between the learner and the interface was an obstacle to having other types of interaction" [p.152]. However, those studies relied on the perceived level of student–systems interactions, while we aim at analyzing the actual quantity and quality of the interaction with the system (as measured by the LMS in use) and its effect on the final learning outcome (Agudo-Peregrina et al., 2014).

More than a decade before Hillman and colleagues emphasized the importance of media in the learning process, Clark (1983) had initiated the great "media debate".[1] Clark (1983, 1985, 1994) argues that the pedagogy applied in a course has a main influence on learning, regardless of media used to deliver the course. Further, he points out that media should be carefully selected and instructors, as well as designers, must be aware of the possibilities provided by the selected media. However, Clark (1994) assumes that a choice of suitable media is more related to the economic (cost-effectiveness) aspect, rather than it has a significant cognitive effect on a learning task. On the other hand, Kozma (1994) argues that researchers should reveal how media influence learning, rather than whether it has any significance at all. Kozma (1994) posits that certain characteristics of media determine their usefulness in the learning process. Utilizing "cognitively relevant capabilities" (Kozma, 1994, p.11) of the selected media, instructors might influence how students obtain and process information, thus directly contributing to the successful completion of a given learning task.

Much of the early studies on distance education were focused on comparative analysis of learning effectivenesses between online and conventional (face-to-face) instructional conditions, aiming at answering the question "whether technology actually works" (Bernard et al., 2004, 2009; Morrison & Ross, 2014). As Bernard et al. (2004) explained, those studies were necessary to inform academics, policy makers and other relevant stakeholders "of the relative value of innovation" [p.379–380]. Summarizing findings from those primary studies, the majority of meta-analyses inferred that methodological quality and the pedagogy features are more significant in predicting learning outcome than technology itself (Lou et al., 2006; Means, Toyama, Murphy, Bakia, & Jones, 2009; Tallent-Runnels et al., 2006), thus supporting Clark's (2000) view on the importance of the technological affordances. However, we tend to agree with Schmid et al.'s (2014) and Clardy's (2009) observation that Clark's (1983) "original argument about the lack of impact of technology used in teaching was formulated during an era when technology was little more than presentational tools". On the other hand, as Bernard et al. (2009) and Clardy (2009) pointed out, except for providing a direction for further research those initial studies that compared distance with traditional learning, did not reveal much about instructional practices that "actually work" in online settings. Comparisons of two or more distance education courses should provide a more comprehensive approach to examining the effect of different instructional practices (Bernard et al., 2009; Clardy, 2009; Roberts, 2011).

The main focus of this study is the analysis of four interaction types (student–student, student–instructor, student–content, and student–system), in online courses, supported by an online learning environment, with a great diversity of tools to support interaction. Although online courses can be designed on the same pedagogical principles as face-to-face courses, they use different approaches to communicating content and conveying interaction between instructors and students, as well as between students and their peers (Smith, Ferguson, & Caris, 2001; Zhu, Payette, & DeZure, 2003).

2.2. Measurement of interactions and effects on learning

Although interactions are considered to be one of the strongest predictors of success in a distance and online education (Donnelly, 2010; Muirhead & Juwah, 2005), there is no precise answer which interaction types are more effective in certain educational situations (Miyazoe & Anderson, 2010). Therefore, various researchers analyzed effects of interaction types on learning operationalized through perceived measures of learning and academic performance. The most commonly used instrumentation to measure interaction types under study here are surveys and interviews (Arbaugh & Benbunan-Fich, 2007; Donnelly, 2010; Marks, Sibley, & Arbaugh, 2005; Rhode, 2009). To a much lesser extent, researchers have relied on measures provided by learning management systems, such as discussion post and/or frequency of content page visits (Agudo-Peregrina et al., 2014; Donnelly, 2010; Ramos & Yudko, 2008).

[1] http://edutechwiki.unige.ch/en/The_media_debate.

2.2.1. Perceived measures of interaction

By using perceived measures of learning, Arbaugh and Benbunan-Fich (2007) analyzed 40 online courses, using the hierarchical modeling technique, and showed that most significant predictors of perceived learning were **student–instructor** and **student–system** interactions. They further argued that instructors must be engaged sufficiently in order to ensure that students successfully complete courses.

Marks et al. (2005) examined importance of student–student, student–instructor and student–content interaction types as predictors of perceived learning and satisfaction with an online course. They also included perceived advantages of online courses, students' personal characteristics and experience with online learning environments as variables into the structural equation modeling analysis. Their findings reveal that **student–instructor** interactions are the strongest predictors of perceived learning. **Interactions among students** were also positively associated with perceived learning, but the strength of the association was much lower than in the case of student–instructor interactions. Only certain **student–content** interactions (i.e., individual and group projects) were significantly associated with perceived learning and students' satisfaction (Marks et al., 2005). Other variables were not significantly correlated to students' perception of learning quality.

2.2.2. Objective measures – A learning analytics perspective

There has been wide adoption of learning management systems in higher education, as well as increased fidelity of data concerning users' activity that can be captured and stored within these systems. Virtual learning environments provide a broad spectrum of possible insights into students' learning progress and the achieved level of knowledge (Ma, Han, Yang, & Cheng, 2015; Macfadyen & Dawson, 2010; Morrison & Ross, 2014; Schmid et al., 2014). On the other hand, the emerging research field of learning analytics offers a great variety of tools and approaches that can help analyze data about learning activities, so-called trace or log data (Siemens, 2012; Siemens et al., 2011). Thus, it is no surprise that analysis of the association between variables of students' behavior (extracted from log data) and learning outcome, attained significant attention recently (Khalil & Ebner, 2015; MacFadyen, Dawson, Pardo, & Gašević, 2014).

Ramos and Yudko (2008) applied a stepwise multiple regression analysis to investigate whether the count of page hits, discussion posts and/or discussion reads (as proxies of student–content and student–student/instructor interactions) can predict final learning outcomes (i.e., the total score on all the assessments students took during a course). Analyzing trace data collected by learning management systems from two online courses, Ramos and Yudko (2008) revealed that the count of page hits (i.e., "the frequency in which each student viewed the content pages at the class site" [p.3]) was the only and highly reliable predictor of quiz success. This finding led them to the conclusion that **student–content** interaction was the most important for predicting learning outcome. Macfadyen and Dawson (2010), on the other hand, included a wide set of behavioral variables, such as the total number of online sessions, total time online, count of messages read/sent. However, the final regression model revealed that the best predictors of students' final grades were the *count of forum postings*, *the count of messages sent*, and *the count of assessments completed*. Observed through the lens of the interaction types theory, Macfadyen and Dawson (2010) confirmed the importance of **student–content** interactions, as well as interactions with peer **students** and presumably **instructors**. Finally, Smith, Lange, and Huston (2012) built a Naïve Bayes model, that revealed the importance of *login frequency*, *engagement with the course website*, *assignment grade*, and *the ability to quickly adopt the content* (i.e., pace) for predicting successful learning outcome (i.e., a grade C or better). Similarly, Morris, Finnegan, and Wu (2005) applied a multiple regression analysis to examine whether online learning activities of students can predict learning success. Their analysis showed that *the count of discussion posts viewed*, *the time spent on viewing discussion posts*, and *the frequency of interaction with content* were the most important predictors of students' final grades.

Although metrics based on the overall use of learning management systems can provide valuable insights into the behavioral patterns of student engagement and can help predict learning outcomes (Romero, Ventura, & García, 2008), these measures do not have a strong theoretical background (De Laat, 2006; Lust, Collazo, Elen, & Clarebout, 2012). This shortcoming, was found as the most significant limitation in Lust et al.'s (2012) systematic review of research of effects of the use of online learning environments on learning. Based on the review of the thirty-four studies, Lust et al. (2012) concluded that students differ in their tool use, and these variations lead to differences in their performance. However, Lust et al. (2012) concluded that there were no theoretically grounded arguments why these student–related variables would have an impact on the learning outcome. Given that the interaction theory (Hillman et al., 1994; Moore, 1989) provides a strong theoretical foundations for better understanding of students' engagement within a learning management system, identifying interaction types from a trace data seems to be a promising approach towards comprehensive analysis of the associations between students' tool use and learning outcome. To address this issue, Agudo-Peregrina et al. (2014) suggest a framework for the analysis of the effects of the interaction types – measured through the use of trace data – on academic performance in both online and blended learning courses. The study did not reveal significant predictors of the academic achievement in case of blended courses. However, Agudo-Peregrina et al. (2014) showed that academic performance mostly depended on **student–instructor** and **student–student** interactions in online learning settings.

2.3. Research questions

The study aims at analyzing the effects of the four types of interaction – i.e., student–student, student–instructor, student–content and student–system – on the learning success. In other words, by using trace data collected by a learning management system, we examine whether the count of and the time spent on each of these four interaction types have an effect on the final learning outcome (i.e., course grades). Thus, we defined our first research question as follows:

RQ 1 *Is there a significant, consistent effect of interaction types (according to Moore (1989) and Hillman et al. (1994)) on the final learning outcome?*

Students' developmental stage might also influence the level of engagement into different types of interaction. According to Zimmerman and Martinez-Pons (1990), students at higher educational levels exhibit greater perceived efficacy. Zimmerman and Martinez-Pons (1990) explained this with the more advanced verbal and mathematical knowledge. Rosário, Núñez, Valle, González-Pienda, and Lourenço (2013) and Cleary and Chen (2009) concluded that deep and meaningful learning decreases as middle school students advance towards the higher grade levels. Shallow learning and the lack of confidence in self-regulation skills are explained with a reduced motivation and a lower level of commitment to the learning tasks. Further, Lust et al. (2012) analyzed findings from two studies, Macfadyen and Dawson (2010) and Woods and Kemper (2009), with rather contradictory findings on the importance of student–content interaction for the final performance. While Macfadyen and Dawson (2010) showed that undergraduate students can benefit from content provided within a learning management system, that was not the case for the group of postgraduate students investigated in Woods and Kemper's (2009) study. Lust et al. (2012) contend that a possible reason might be a higher level of experience and metacognitive skills that postgraduate students already had, in contrast to the experience and skill levels of the undergraduate students. Therefore, we defined our second research question as follows:

RQ 2 *Is there a significant effect of a course level with respect to the interaction types supported on students' academic achievement?*

3. Method

In this section, we describe the data collection process and measures used in the study. Moreover, we explained the procedure followed to conduct the study and the analysis method performed on the collected data.

3.1. Sample and study design

The study reported in this paper followed correlational (i.e., non-experimental) design and is a case study in nature (Bryman, 2012), which is a commonly applied design in the learning analytics research field (e.g., Blikstein, 2011; Eckles & Stradley, 2012; Gašević, Zouaq, & Janzen, 2013; de Laat & Schreurs, 2013). Data were obtained from a master's in information systems program at an online public university in Canada, for the period from 2006 to 2012 (i.e., since the implementation of the current learning management system – Moodle, until the time of the data collection). The complete program is delivered using distance education instructional design, with standard requirements for obtaining master's degree in information systems, which are in line with the North American educational system. Course content and learning activities are conveyed by using the Moodle learning management system. The program typically has two intakes per year and the vast majority of students enrolled in to the program worked full-time and studied part-time.

The sample included 29 courses with 204 offerings, over the period of six years (2006–2012), where each course was categorized as either foundation ($N = 65$), core ($N = 95$), or elective ($N = 43$). Foundation courses were designed to provide students with skills required for the successful completion of the master's program (i.e., to obtain prerequisites for core and elective courses). Core courses were comprised of technical (e.g., human computer interaction, database design) and managerial courses (e.g., information systems project management), designed in a way to develop students' knowledge in the core disciplines of information systems. Elective component allowed students to select specialized courses (e.g., affective, social, or mobile computing) of direct relevance for their final master's research. Table 3 presents students' enrollments (median, 25th and 75th percentile) per course offering belonging to each of three categories. Each course was three credits worth, while grades in the program were from F to A+. According to the university policy, the grades were converted into grade points in the range from 0 to 4 where each grade increase resulted in an increment of 0.33 grade point (e.g., from B– to B). It is important to note that both A and A+ letter grades were worth 4 grade points according to the university grading

Table 1
Measurements used in the study.

Measure	Description
SSCount	Total count of student–student interactions for a student, per course
SCCount	Total count of student–content interactions for a student, per course
STCount	Total count of student–teacher interactions for a student, per course
SSyCount	Total count of student–system interactions for a student, per course
SSTime	Total time spent on student–student interactions for a student, per course
SCTime	Total time spent on student–content interactions for a student, per course
STTime	Total time spent on student–teacher interactions for a student, per course
SSyTime	Total time spent on student–system interactions for a student, per course

Table 2
Characteristics of study participants ($N = 352$).

Variable	Median (25%, 75%)
Number of courses per student	5 (3, 8)
SSCount	60 (23, 147)
STCount	28 (9, 72)
SCCount	**475 (292.5, 786)**
SSyCount	100 (62, 158)
SSTime (sec)	1848 (205.5, 15,243.5)
STTime (sec)	746 (88, 7990.5)
SCTime (sec)	**81,345 (33,469, 190,534)**
SSyTime (sec)	766 (83, 7364.5)

Bold represents the highest values.

Table 3
Students enrolled per each course group.

Course group	Median (25%, 75%)
Core courses	12 (8, 17)
Elective courses	7 (4, 12)
Foundation courses	12 (9, 17)

policy. For foundation and core courses to be counted toward the degree, the minimal grade students could get was B− (i.e., 2.67), while for elective courses it was C+ (i.e., 2.33). From the initial sample, we excluded records for students who had not obtained any credit, i.e., those students who were enrolled into the first courses at the time of the data collection. Therefore, we used sample of 352 students to extract variables for our analysis (Table 2).

3.2. Data collection and measurements

Students' interactions within the learning management system were coded according to classification suggested by Moore (1989) and Hillman et al. (1994). With respect to the measures used to address identified research questions, our approach is somewhat similar to that of Agudo-Peregrina et al.'s (2014). Specifically, the four interaction types analyzed are recognized in Agudo-Peregrina et al.'s (2014) study as measures based on the agents involved in the learning process. However, besides the quantity (i.e., counts of each interaction type), we also analyzed time students spent on interactions with content, system, instructor and their peers as commonly done in the field of learning analytics (Table 1). Descriptive statistics (median, 25th and 75th percentile) for each measure are presented in Table 2. A final course grade was used as a dependent variable.

3.3. Study procedure

The initial step in our analysis was to classify the trace data according to the proposed intraction types (Section 3.2). Identifying interactions between users of the learning management system was a quite straightforward process (Table 6). However, classifying those interactions as student–student or student–instructor was a challenging task. We assumed that interactions between students and instructors might occur within discussion forums, blog posts (sharing comments), exchanging messages within the learning management system, chats, and wikis. Therefore, whenever a communication occurred between two users, we inspected whether an instructor was involved in the communication. In case of a direct contact with the instructor (messages and/or chat), the Moodle log data provided us with an explicit information about the participants in the communication. However, if a student created a post in a discussion forum, that would be classified as student–student interaction, as long as no instructor responded to that particular post.

Another, more complex challenge, was to calculate time on task (i.e. time spent on each interaction activity) (Kovanović et al., 2015). Since the Moodle learning management system stores a timestamp for each record in its database, we calculated time on task by subtracting timestamp of the current activity from the timestamp of the first subsequent interaction. However, trace data did not contain an indicator when a learning session ended, therefore, some of the values were much above reasonable expectations for the particular activity (e.g., more than two days spent on the course initial page). Those values were considered outliers, and thus, we developed the following heuristic for handling them: i) for each outlier value, we calculated a median time spent on that activity type (e.g., chat) for a given student in a selected course, ii) finally, the outlier values were replaced with the calculated median value. We chose the median value as a measure of students' central tendency (i.e., a typical amount of time spent on each interaction type), as the median is not seriously affected by outlying values and heavy asymmetry (Field & Hole, 2003). Finally, for every student in each course we computed the total count and time spent on each type of interactions.

3.4. Statistical analysis

The structure of our data consists of both nested (hierarchical) and crossed (interacting) variables. The initial model included 18 fixed-effects variables: course group, course name within course group, the four count variables, the four time variables, and the interactions between the course group and each count or time variable. We therefore fitted hierarchical linear mixed models using the restricted maximum likelihood (REML) estimation (Littell, Milliken, Stroup, Wolfinger, & Schabenberger, 2006; Milliken & Johnson, 2004) with student grade in the course as the response variable.

Pre–analysis data exploration included plots of grade against each of the time and count variables, with simple linear regression lines overlaid. These plots showed an extremely right-skewed distribution to the count and time variables and a distinctly nonlinear relationship between each of them and the grade response, resulting in numerous instances of predicted values above the maximum possible grade, 4.00. Applying a simple log transformation to each count and time variable removed most of the nonlinearity (Kutner, Nachtsheim, & Neter, 2004). We therefore used these log-transformed explanatory variables in all models instead of their original form.

Next, we reduced the model size by using a version of backward elimination (Kutner et al., 2004) respecting the marginality of the model[2] and using the corrected Akaike Information Criterion (AICc) to select a final model (Hastie, Tibshirani, & Friedman, 2009). Specifically, we first fit the full model with all 19 explanatory variables. We found its AICc, and obtained *t*-test statistics and p-values for each variable (main effect or interaction). We identified the variable with the largest p-value and removed it from the model if the resulting model would satisfy marginality; i.e., if it was either an interaction term or a main effect term that was not involved in any interactions. If the candidate variable did not satisfy these conditions, we considered the variable with the next smallest p-value in turn until a satisfactory candidate was found and could be removed. We then iterated this variable-elimination process on until the model was empty, resulting in a sequence of 19 candidate models. Finally, we selected the model with the smallest AICc from among this sequence as our final model. Note that in all models the same random-effects terms were present, so that comparing information criteria is valid under REML estimation (Littell et al., 2006). It is also important to note that in addition to constructing and fitting the model, we also constructed a *null (empty) model*, with only random effects and no fixed effects included. A comparison of this model with the fixed-effect models allowed us to determine whether the counts and time spent on the selected types of interactions predicted learning outcomes (i.e., course grade) above and beyond the random effects.

Our use of linear mixed models was carefully considered. While hierarchical linear mixed models assume that data are normally distributed around their respective means, our response, grade, is a discrete numerical variable with only seven levels. We therefore cannot expect the normality assumption to hold exactly. However, we do not believe that this is a serious flaw in our modeling process, because we have taken great care to fit an appropriate random-effects portion of the model that respects the hierarchical nature of the data, and we have attempted to ensure that the data fit the fixed-effect portion of the model by the use of the log-transformation on the counts and times. Fang and Loughin (2012) demonstrate in the context of a different hierarchical problem that correctly modeling the random effects while incorrectly assuming normality of the data leads to *much* more reliable tests for effects than correctly modeling the distribution while mis-modeling the random effects. Because reliable models for clustered data from discrete distributions are limited and are much more difficult to work with (Molenberghs & Verbeke, 2005), we chose to use a modeling context that was accessible and likely to provide a good approximation.

Analyses were performed using PROC MIXED in SAS Version 9.3 software for statistical analysis.

4. Results

The final model included *course group*, *course within a course group*, *count of student–content interactions*, *time spent on student–system interactions*, as well as the *interaction effect between course group and time on student–teacher interactions, and count of student–student interactions* (Table 4). A comparison of AICc values for the null (AICc = 1224.8) and the chosen model (AICc = 1159.7) provided a strong evidence favoring the model that included fixed and random effects (Burnham & Anderson, 2002). The random part of the three-level model indicates that the variance between students (*Wald* $z = 7.75$, $p < 0.001$) as well as between particular course offerings within each course and each course group (*Wald* $z = 5.92$, $p < 0.001$), was significantly different from zero. Moreover, the intraclass correlation coefficient indicates that almost 18% of the variability in the learning outcome was accounted for by individual differences – related to the individual's overall grade average point across all courses (i.e., overall GPA) – while 22% is explained by differences between course offerings. The remaining 60% is variability of individual student performances within different classes.

The hierarchical linear mixed model (Table 4) further revealed that the count of the student–content interactions ($F(1, 1443) = 7.15$, $p = 0.008$) and time spent on student–system interaction types ($F(1, 1443) = 5.68$, $p = 0.017$), were significantly associated with the students' grades. Holding the values of all other variables constant, the effect of time spent interacting with the system was associated with a positive effect on the final learning outcome, while the higher quantity of student–content interactions was associated with a negative effect (Table 4). Further, significant effects were found for the remaining fixed effects: a particular course within a course group ($F(26, 175) = 4.96$, $p < 0.0001$), course group (F(3,

[2] Model marginality means occurs when the presence of a particular interaction in the model implies that all of its constituent ("main") effects are also in the model. For example, a model with A*B also retains both A and B. See (Nelder, 1977) for details.

Table 4
Solution for interaction types supported.

	β	SE	95% CI		g
			Lower	Upper	
courseGroup (C)	3.81***	0.08	3.66	3.97	
courseGroup (E)	3.41***	0.18	3.05	3.77	
courseGroup (F)	3.82***	0.07	3.67	3.96	
SCCount	−0.09**	0.03	−0.16	−0.02	**.14**
SSyTime	0.03*	0.02	0.005	0.05	**.12**
STTime*courseGroup (C)	−0.04**	0.01	−0.06	−0.01	**.15**
STTime*courseGroup (E)	0.02	0.02	−0.02	0.06	.05
STTime*courseGroup (F)	0.02	0.01	−0.009	0.05	.07
SSCount*courseGroup (C)	0.18***	0.03	0.12	0.24	**.30**
SSCount*courseGroup (E)	0.15**	0.05	0.06	0.25	**.17**
SSCount*courseGroup (F)	0.05	0.04	−0.03	0.13	.06

*p < 0.05, **p < 0.01, ***p < 0.001.
β − estimated slope or mean for the factor variable, SE − standard error, CI − confidence intervals, g − Hedges' g effect size.
Estimated values for course groups are marks for every group, holding the values of all other variables constant. Estimated values for counts and time on task are base-10 log values, having that a one unit increase/decrease in the log-value corresponds to the 10-fold increase/decrease in the final grade.
Bold represent ranges for Hedge's g effect size are Small > 0.1, Medium > 0.3, Large > 0.5. Small to medium effect sizes.

Table 5
Differences between course groups with respect to fixed effects.

Fixed effect	Groups	DF	F	Pr > F
SSCount				
	C vs. E	1443	0.25	.620
	C vs. F	**1443**	**9.61**	**.002**
	E vs. F	1443	3.44	.064
STTime				
	C vs. E	**1443**	**5.30**	**.021**
	C vs. F	**1443**	**8.60**	**.003**
	E vs. F	1443	0.00	.969

Bold represents statistically significant values.

175) = 1289.96, $p < 0.0001$), the interaction between the time spent on the student–teacher interaction and the course group ($F(3, 1443) = 3.74$, $p = 0.010$), and the interaction between the count of student–student interactions and the course group ($F(3, 1443) = 12.94$, $p < 0.0001$). Table 4 provides further details for each course group.

Considering significant effects of an interaction between course group and time spent on student–instructor interactions and between course group and the count of student–student interactions, we performed further analysis to understand the nature of these interactions. Table 5 shows that the association between student–student interaction count and final grade is largest in core courses, slightly lower in elective courses, and not statistically significant in foundation courses. Table 5 shows direct comparisons between these effect magnitudes, finding that there is a statistically significant difference between the core and foundation courses ($F(1, 1443) = 9.61$, $p = 0.002$) and only the marginally significant difference between elective and foundation courses ($F(1, 1443) = 3.44$, $p = 0.064$). Table 5 also shows a significant negative association between time spent in student–course interaction and final grade on core courses, but no significant associations for foundation or elective courses. Comparing the magnitudes of these effects in Table 5, we find a statistically significant difference between the core and elective courses ($F(1, 1443) = 5.30$, $p = 0.021$), as well as between core and foundation courses ($F(1, 1443) = 8.60$, $p = 0.003$).

The comparison of the estimated least squares mean[3] for the core ($M = 3.71$, $SD = 0.02$), foundation ($M = 3.69$, $SD = 0.03$), and elective ($M = 3.81$, $SD = 0.04$) courses, revealed a statistically significant difference between the mean grades in elective and core courses ($t(175) = -2.09$, $p = 0.038$) and between the elective and foundation ($t(175) = 2.23$, $p = 0.027$) courses. However, the results did not show any statistically significant difference in mean grades between the core and foundation courses ($t(175) = 0.48$, $p = 0.63$).

5. Discussion

5.1. Interpretation of the results with respect to the research questions

The results of our study further contribute to the understanding of importance of the interactions in an online and distance educational settings (e.g., Bernard et al. 2009; Lou et al. 2006; Muirhead & Juwah, 2005; Woo & Reeves, 2007). Moreover, we

[3] The β values for the three course group levels are computed as intercepts. This means that they assume that all explanatory variables are fixed at zero, which may be very far away from the majority of the values and hence potentially not a representative estimate. The Least Squares Means are computed at the overall mean values of each of the explanatory variables, therefore they are more likely to be "central" values for the marks.

also revealed that educational level and context of a particular course have a significant impact on interaction types supported, and therefore on their importance for the student achievement.

Among analyzed interaction types, time spent on *student–system* interactions revealed the most significant, consistent and positive effect on the final achievement (RQ1). It should be pointed out that estimated values (Table 4) represent the change in course grade associated with a *10-fold increase* in the respective count or time. Comparing the estimated values, we can conclude that count of student–student interactions had consistently larger effects than other variables, per 10-fold increase, even though the change was not deemed to be constant for all course groups. This finding partially supports Arbaugh and Benbunan-Fich's (2007) findings, who showed that only student–system interactions were associated with a higher level of learning perception and satisfaction with the underlaying medium used to deliver the course. We further tend to agree with Arbaugh and Benbunan-Fich's (2007) conclusion that successful learning in online settings requires high digital proficiency from learners, as well as engaging and user-friendly systems to support this type of interaction (Carroll, Booth, Papaioannou, Sutton, & Wong, 2009; Styer, 2007). Finally, the importance of the underlaying medium, used to deliver the courses, further supports Kozma's (1994) view of technology in online and distance education.

We also revealed significant, although negative, correlation between final grades and *student–content* interactions (RQ1). The vast majority of studies that analyzed various interaction treatments in online learning settings (Bernard et al., 2009; Roberts, 2011; Tallent-Runnels et al., 2006), concluded that online courses should provide a good support for interaction with highly engaging and interactive content in order to support learning and foster learning achievement. However, our findings are somewhat contradictory. A possible rationale for such a finding could be that inherently weaker students needed to repeatedly re-examine the course content. Nevertheless, this finding warrants further research that should provide a deeper insight into the course design and potentially reveal more reliable explanations.

Another important aspect of our study is the significant interaction between time spent on *student–instructor* interactions and the course level, as well as between the count of *student–student* interactions and the course level (RQ2). The literature on distance and online learning almost unequivocally argues for the importance of instructors' supportive role and constant interaction with students, as well as the collaboration between peer learners as most prominent ways for fostering learning in online contexts (Bernard et al., 2009; Borokhovski et al., 2012; Darabi, Liang, Suryavanshi, & Yurekli, 2013; Gikandi, Morrow, & Davis, 2011; Koch, 2014; Roberts, 2011). Moreover, online students tend to consider interaction with instructors to be of great importance for learning online and the single most important component of online course design and delivery (Anderson, 2003; Bernard et al., 2009; Koch, 2014). However, our study provides more "fine-grained" insight into the importance of these two types of interactions within the specific course group. Specifically, in the case of the *core courses*, student–instructor interactions (i.e., time spent on communication with instructors) had a significant, although *negative effect* on the students' grades, whereas in *elective* and *foundation* courses, effect was positive and *not* significant. On the other hand, the positive effect of student–student interactions (i.e., count of various messages exchanged between students and their peers) for the core and elective courses was stronger than any other interaction type supported (Table 4).

Our results indicated significant effects of the characteristics of core, elective and foundation courses on the academic performance in the students in our sample.[4] The foundation courses (see Section 3) likely provided students with basic knowledge needed to successfully complete the course work and meet prerequisites for pursuing the master's degree (i.e., they were taken by the students who did not have undergraduate degrees in the field of the master's program). Therefore, it seems that the foundation courses were more content oriented, focused on content assimilation and knowledge acquisition, rather than higher-order learning outcomes. This further means, that communications between students and instructors, as well as among students, would not be the main focus in the foundation courses. On the other hand, elective courses tended to attract students with similar research interests, of close relevance to their final master's research, which likely led to an increased level of communication between peers. Finally, the core courses likely assumed an increased teaching presence, and more intensive communication between instructor and students. However, time spent on student–instructor interactions had a negative effect on the students' grades, which supports Lou et al.'s (2006) observation about the complexity of relationship between the course design and media used to deliver the course content. In fact, Lou et al. (2006) revealed that using media to communicate with instructor (e.g., telephone), negatively predicted student achievement. This finding can probably be justified by the increased needs of those students who straggle with the course material for an increased instructional support.

The significant statistical interaction between the student-activity types supported and course group, might be further affected by students' developmental level (Rosário et al., 2013; Zimmerman & Martinez-Pons, 1990). The lack of the effect of student–student and student–teacher communication in the foundation courses might be induced by a lower level of self-efficacy to interact with others (Cho & Kim, 2013; Wang, Shannon, & Ross, 2013). A possible reason for this could be a low level of familiarity with a learning environment. A considerable proportion of the students in our sample had their undergrad degrees awarded from traditional face-to-face programs, which were often outside Canada in languages other than English, whereas these courses required students to study in a fully-online mode. Later on, through the course work, students were likely gaining more domain specific knowledge, and building connections with their colleagues (i.e. establishing social presence (Garrison, Cleveland-Innes, & Fung, 2010)), which might lead to increased peer-to-peer communication in the core

[4] Given the correlational nature of the study, causality could not be inferred from the analyses performed. Therefore, the interpretation of our findings is based on the contemporary research literature.

and elective courses. Another possible reason could be the lack of scaffolds for interaction with others (Cho & Kim, 2013). Thus, a potentially relevant line of research would include coding courses based on their level of scaffolding for interaction with others. The analysis would include examination whether scaffolds for interaction with peer students moderate the association between the social interactions and academic performance.

5.2. Implications for research and practice

Current research on online and distance education contend that interaction treatments that include cooperative and collaborative work, thus fostering student–student interaction, tend to outperform other types of treatments (Bernard et al., 2009; Borokhovski et al., 2012; Darabi et al., 2013; Lou et al., 2006). Investigating further student–student interactions from the two perspectives – i.e., contextual and designed interactions – Borokhovski et al. (2012) showed that simply providing means for interaction is not enough. Specifically, Borokhovski et al. (2012) revealed that the most effective student–student interactions are those that are intentionally designed to effectively support collaboration and cooperation between students. In our study, we were able to conclude that student–student social interactions in the courses at the higher program level (i.e., core and elective courses vs. foundation courses) were most strongly associated with learning outcomes. If this association is, indeed, causal then this finding suggests that institutional strategies for learning and teaching should be created to promote effective pedagogical approaches to designing and guiding interactions among students.

Using quantitative research methods, we were able to show strong association between student interactions within an online learning environment and the students' academic achievement. Nevertheless, various models for studying online learning and teaching that allow for the analysis of different qualitative dimensions of the interaction were developed. For example, the community of inquiry model (Garrison et al., 1999) recognizes three types of presence (i.e., teaching, cognitive, and social presence) that shape educational experience in online settings, whereas, Gunawardena et al.'s (1997) framework for interaction analysis in computer mediated communication, defines five levels of knowledge construction. Thus, further refinement of the four types of interactions to account for different qualitative dimensions, could provide a deeper insight into our findings.

The study employs learning analytics methods (Phillips et al., 2012; Siemens et al., 2011) to assess the relationship between the quantity and the quality of various types of interactions and the final course grade. Although findings indicate a need for the further investigation, we showed that learning analytics can produce results that are comparable to those measured with self-reported instruments. Thus, the study further supports Agudo-Peregrina et al.'s (2014) conclusion on the importance of using data logged by learning management environments in order to better understand learning and teaching in online settings. Specifically, learning analytics methods allow for higher level assessments of the educational programs without a need to interfere with the educational processes and learning activities of learners. Nevertheless, it is indicative that extracted effect sizes (Table 4), are on average almost half as large as those reported in Bernard et al.'s (2009) study. Bernard et al. (2009) reported an average g effect sizes of 0.49 for student–student, 0.32 for student–instructor, and 0.46 for student–content interactions, while we obtained medium to small effect sizes with $g = 0.30$ being the largest effect size found for student–student interactions in core courses. This finding is a subject to a further research, that should investigate the cause for the observed differences in the effect sizes.

Evidence about the complexity of the relationship between pedagogy and media used to deliver online course is provided in two meta-analysis, conducted by Lou et al. (2006) and Bernard et al. (2009). While Bernard et al. (2009) found some evidence that supports Anderson's (2003) equivalency theorem, and Kozma's (1994) view of importance of media in predicting student achievement, Lou et al. (2006) reported contradictory results. In order to assess the relative importance of methodology, applied pedagogy and media, Lou et al. (2006) identified 8 media features (e.g., use of e-mail, videoconferencing), 13 methodology features (e.g., treatment duration, effect size estimation, instructor and student equivalence), and 9 pedagogy features (e.g., problem-based learning), categorized into three respective groups. They showed that most of the variance in learning outcome was explained by methodological quality and pedagogy. Therefore, their findings "support Clark's (2000) view that research methodological quality often confound studies on technology effects and that pedagogy features are more important than media in predicting student achievement" (Lou et al., 2006, p. 2). In our study, we accounted for developmental factors observing the association between a course level and an academic achievement, showing that the educational level should be considered an important component in course design and delivery. Nevertheless, future research should consider coding various different pedagogies/media features (e.g., as suggested by Lou et al. 2006) in order to investigate complex association between instructional practices and media affordances that enable better support for learning in online settings.

The negative relationship between student–instructor interactions and the final learning outcome at the core course level, and no significant association on the foundation and elective course levels, are perhaps the most intriguing findings of this study. A majority of the existing research on online learning highlights the importance of instructors' involvement in terms of constant monitoring, provision of formative, timely, and personalized feedback, as well as guiding students' collaboration and cooperative work Darabi et al. (2013); Tallent-Runnels et al. (2006); Koch (2014); Gikandi et al. (2011). Therefore, further investigation is also needed to examine the role of instructor in online learning settings and the association between the quality and quantity of student–instructor interaction and the course grade. A possible reason for the negative association could be that those students who reach out to the instructors also struggle the most. However, this warrants further research. A promising approach to study this phenomenon is Ma et al.'s (2015) interaction activity model that recognize various aspects of instructors' engagement in online courses. Coding activities using Ma et al.'s (2015) model could reveal which of the proposed teaching and learning activities have the most impact on the association between student–instructor interactions and learning achievement.

Our results further revealed the importance of the course context for predicting students' academic achievement. Moreover, the course context showed to be even more important than the individual differences. Although we have not further investigated the relationship of specific courses with both the interaction types supported and academic performance, the significant effect of the course within a course group on the final grade certainly warrants further research. Instructors' teaching preferences, course design, various assessment types supported, and course domain, are some of the potentially relevant factors that might influence types of communication supported within a specific course (Lockyer, Heathcote, & Dawson, 2013; Lust et al., 2012). Garrison and Cleveland-Innes (2005) argue that students' approach to learning (i.e., shallow vs. deep learning), and interaction types supported are significantly influenced by the course design and teaching approach. They showed that in order for meaningful learning to occur, and to increase students' qualitative engagement, strong facilitation and scaffolding is needed. Thus, further investigation is necessary to explain the importance of various course design and delivery aspect on the level of interactivity within online and distance courses.

5.3. Limitations

First and foremost, this was an observational study, lacking in any randomization of learning environments to students or course offerings. We therefore cannot establish directional causality in any of the observed associations within the study. Next, we analyzed students' interactions in more than 200 course instances, over a six-year period. However, those courses belong to a single master's program in information systems, within an online Canadian university. In order to further extend external validity of our findings, it is highly important to perform similar analyses on datasets obtained from other universities and degree programs in other subject areas (e.g., business, health, arts). Moreover, we observed courses as "black boxes"; that is, we did not analyze course design, pedagogy and learning strategies applied within each course under study here. Finally, we analyzed active participation (i.e., time spent and quantity of four types of interactions), however, deeper understanding of vicarious interactions Sutton (2001); Wise, Hausknecht, and Zhao (2013) is also needed in order to better explain other variables that might predict learning outcome.

Appendix A

Table 6
Mapping Moodle logs to the four interaction types analyzed within the study

Interaction type	Event		Interaction type	Event	
	Module	Action		Module	Action
Student–Student	chat	view	Student–Content		
	chat	talk		book	update
	chat	report		book	generateimscp
	chat	add		book	add
	forum	view discussion		chat	view all
	forum	add post		choice	view
	forum	add discussion		choice	view all
	forum	update post		choice	choose
	message	write		course	report log
	message	history		course	view
	oublog	add comment		course	report stats
Student–Teacher	chat	view		course	report outline
	chat	talk		course	report participation
	chat	report		course	report live
	chat	add		course	user report
	forum	view discussion		data	add
	forum	add post		data	view all
	forum	add discussion		data	update
	forum	update post		data	view
	message	write		forum	view forum
	message	history		forum	update
	oublog	add comment		forum	view forums
	questionnaire	view		forum	user report
	questionnaire	view all		forum	search
	questionnaire	submit		forum	delete discussion
Student–System	calendar	add		forum	delete post
	calendar	delete		forum	add
	calendar	edit		forum	move discussion
	calendar	edit all		forum	delete attachment post
	calendar	delete all		glossary	view

Table 6 (*continued*)

Interaction type	Event		Interaction type	Event	
	Module	Action		Module	Action
	course	update		glossary	view all
	course	new		glossary	update
	course	delete		glossary	add entry
	course	add mod		glossary	add comment
	course	update mod		glossary	update comment
	course	delete mod		glossary	update entry
	course	editsection		glossary	delete comment
	course	enrol		glossary	delete entry
	course	unenrol		glossary	add category
	discussion	mark read		label	add
	forum	mail blocked		label	update
	forum	subscribe		notes	view
	forum	mail error		oublog	view
	forum	subscribeall		oublog	view all
	forum	unsubscribe		oublog	add post
	forum	unsubscribeall		oublog	edit post
	forum	stop tracking		ouwiki	view all
	forum	start tracking		ouwiki	view
	forum	mark read		ouwiki	edit
	forum	mail digest error		ouwiki	history
	forum	view subscribers		ouwiki	viewold
	library	mailer		ouwiki	diff
	message	add contact		ouwiki	entirewiki
	message	remove contact		ouwiki	comments
	message	block contact		quiz	view
	message	unblock contact		quiz	report
	ouwiki	wikiindex		quiz	view all
	ouwiki	reportsuser		quiz	attempt
	user	login		quiz	review
	user	logout		quiz	continue attempt
	user	view		quiz	preview
	user	update		quiz	close attempt
	user	view all		resource	view
Student–Content	annotation	summary		resource	view all
	annotation	list		resource	add
	annotation	summary		resource	update
	annotation	create		upload	upload
	annotation	delete		upload	infected
	annotation	update		wiki	edit
	assignment	view		wiki	view
	assignment	view all		wiki	view all
	assignment	upload		wiki	add
	assignment	view submission		wiki	update
	blog	view		wiki	links
	blog	add		wiki	attachments
	blog	delete		wiki	info
	blog	update		wiki	diff
	book	view		wiki	
	book	view all		wiki	sitemap
	book	print		wiki	bogus

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