MASTER THESIS

Exploring higher-order thinking in a MOOC:

Automatic identification and the impact on attrition

Yuniar Fajar Perdhana

SUPERVISORS
Dr. Bas Kollöffel
Dr. Stéphanie van den Berg

Educational Science and Technology
Faculty of Behavioural, Management, and Social Sciences
University of Twente

SEPTEMBER 2018

UNIVERSITY OF TWENTE.

Exploring higher-order thinking in a MOOC: Automatic identification and the impact on attrition

Summary

Massive open online courses have emerged as one of the most potential tools in enabling access for people all over the world to education. However, MOOCs are often criticized, especially in terms of the low-quality learning experience and the high dropout rate. This is possibly because of the lack of information regarding learners' progress. As online discussions contain a lot of information about learners' thoughts, analysing learners' posts can provide a better understanding of how they think, learn, and predict their performance in the MOOC. The emergence of text mining and machine learning technologies makes this analysis possible, regardless of the massive number of learners and posts generated.

This study aims to explore higher-order thinking processes in a MOOC. First, a supervised text classification model was designed, trained, and validated to automatically identify learners' higher-order thinking processes from the discussion posts. Following this, a survival analysis was performed to investigate the impact of learners' higher-order thinking processes towards retention in the MOOC. The results show that the supervised text classification model can classify learners' comments from an online discussion into three levels of thinking with 62% accuracy and Cohen's kappa of 0.58; whereas lower-order thinking and higher-order thinking can be distinguished with 90% accuracy and 0.76 Cohen's kappa. We also found that learners' who did not engage in higher-order cognitive efforts through their participation in the online discussion were 75.68% more likely to drop out from the course compared to those who did.

Keywords: Massive open online courses, online discussions, text classification, drop out

Acknowledgements

I took a long and circuitous route towards the completion of this master thesis. It was a very challenging project as it required me to learn a lot of things, yet I enjoyed the process. During this project, I've found my interest with learning analytics and machine learning continued to grow, therefore, this project is probably just a first part of more works on this field in the future.

I would like to thank my first supervisor, Dr. Bas Kollöffel, for his patience, support, and helpful feedback throughout this project, especially when I felt lost and confused during the completion of this final project. I would also like to thank my second supervisor, Dr. Stéphanie van den Berg, for her constructive feedback, motivation, and encouragement for me to work on this project.

I convey my special acknowledgement to Jan Nelissen, The University of Twente Scholarship Committee, and Nuffic Neso Indonesia for providing me with the Orange Tulip Scholarship which made it financially possible for me to study at the University of Twente. I also thank Eduardo Hermsen for allowing me to carry out my final project on one of the University of Twente MOOCs and providing me with the datasets and assistance throughout the project.

Finally, many thanks to my family and friends for their support during my study in the Netherlands. Special thanks to my wife, Diesta Dhania Pertiwi, for her unconditional love and for keeping my spirit up.

Table of contents

1. Introduction

In recent years, online learning has gained popularity in the fields of education and training. As information and communication technology advances, more and more organisations and educational institutions have begun to provide courses through digital and network technologies, resulting in a growing number of learners enrolled in online classes (Allen & Seaman, 2016). Massive open online course (MOOC), as a recent variant of online learning which aims to offer online courses to a large number of participants, even has received a considerable attention due to its capability to enable access for people all over the world to education provided by top universities and organisation through the internet mostly for free of charge. In 2017, the number of users enrolled in MOOCs has reached 78 million within 9,400 courses from 800 institutions (Shah, 2018).

Despite being claimed as a means of democratising education, innovative disruption, and revolution in higher education (Dillahunt, Wang, & Teasley, 2014; Friedman, 2013; Skiba, 2012), MOOCs have been criticized in terms of its quality. Besides the issue regarding low completion rate (Alraimi, Zo, & Ciganek, 2015; Jordan, 2015), there is also an on-going debate whether MOOCs can facilitate deep and meaningful learning that promotes the acquisition of higher-order thinking (Abeer & Miri, 2014). Some critics argued that this is because MOOCs mostly resemble the instructor-centred approach which puts learners as passive absorbers of information (Steffens, 2015; Yousef, Chatti, Schroeder, Wosnitza, & Jakobs, 2015). Moreover, Vardi (2012) also criticised the absence of serious pedagogy in MOOCs, as most lectures are merely delivered via short videos interleaved with online quizzes.

On the other hand, assessments and feedback, as important components in learning, are considered insufficient in MOOCs. While in a traditional classroom environment the teacher can continuously evaluate learners' progress through different kinds of formative assessments (e.g., observation, questioning, and discussion) and provide feedback accordingly, these methods might not be suitable in massive online learning environment due to the large ratio between instructors and learners. Formative assessment in MOOCs is often superficial rather than at a deeper level of applying knowledge to solve a challenging problem and the feedback given is often too simple on declarative knowledge items, such as feedback on multiple choice quiz questions (Spector, 2017; Yousef et al., 2016). Currently, there are three main types of assessment in MOOCs, namely e-assessment, peer-assessment, and self-assessment (Yousef et al., 2016), but these ways of assessment lack in accurate information about the learning process in MOOCs (Smalbergher, 2017).

Czerkawski (2014) identified that learners' quality of thinking is also an essential part of a meaningful learning process. As learners actively using higher-order level of cognitive functions in a learning process to interpret the material, the content becomes more relevant and significant for them (Offir, Yev, & Bezalel, 2008). Higher-order thinking also indicates learners' cognitive engagement within a learning activity (Zhu, 2006); while it was found that the more cognitively engaged learners have a lower risk of dropout in MOOCs (Wen, Yang, & Rosé, 2014). Assessing learners' higher-order thinking, therefore, would give deeper insights into the learning processes, thus, enables the opportunity for instructors to provide more timely and informative feedback resulting in a better learning experience.

It is still a big challenge to evaluate the process of thinking and learning in MOOCs. However, the rich data generated from the platform can be utilized to analyze learners' behaviours. As research found that social interaction contributed to learning, online discussion becomes an important component in online learning because it allows learners to express their thoughts and maintain discussions with their instructors and peers related with their learning process (Cobo et al., 2011). Research that shows evidence of higher-order thinking in online discussions also suggested that such forums may facilitate certain kinds of learning due to the fact that online discussions allow learners to reflect, structure, and organize their thoughts (Garrison, Anderson, & Archer, 2000; McLoughlin & Mynard, 2009).

Furthermore, the emergence of text mining, language processing and machine learning technologies makes the content analysis of online discussions in MOOCs, which is often large-scaled and asynchronous in nature, easier (Wang, Wen, & Rosé, 2016). Such technologies have been applied in different studies such as to automatically assess learners' sentiment (Tucker, Pursel, & Divinsky, 2014) and cognitive engagement (Wen et al., 2014). Smalbergher (2017), on the other hand, developed a coding schema and used it to automatically identify learners' quality of thinking in a MOOC using a supervised text classification program written in Python. The current study aims to implement the coding schema to develop a supervised text classification model in order to identify higher-order thinking processes in a different MOOC. Additionally, considering that low completion rate is a major issue in MOOCs, this study also examined the impact of higher-order thinking towards retention in MOOCs.

2. Theoretical framework

2.1. Higher-order thinking

Despite there is an agreement that thinking can be distinguished into higher-order and lower-order, the term higher-order thinking is described differently in literature. Brookhart (2010) identified that definitions of higher-order thinking fall into three categories, namely in terms of transfer which focus on the application of knowledge to a new context, critical thinking, and problem-solving. The definition of higher-order thinking by Newmann (1990) involves the three categories. He described that higher-order thinking demands students to not only routine and mechanistic application of prior knowledge, but also challenges them to interpret, analyze, or manipulate information to solve a novel problem. Lewis and Smith (1993) further suggested higher-order thinking as an encompassing term that includes problem-solving, critical thinking, creative thinking, and decision making. The proposed definition was: “higher-order thinking occurs when a person takes new information and information stored in memory and interrelates and/or rearranges and extends this information to achieve a purpose or find possible answers in perplexing situations” (p. 136).

Learning, on the other hand, requires certain cognitive activities to process, organize, and retrieve information. Mayer (2014) proposed a model which represents three cognitive processes that happen in a meaningful learning process: selecting relevant material, organizing selected material, and integrating selected material with existing knowledge. Selecting process occurs when a learner focusing attention on appropriate objects in the presented material and bringing the material into the working memory in the cognitive system (Mayer, 2014). It is then followed by organizing process which involves building structural relations between the selected information (Mayer, 2014). The final process is integrating and building connections between incoming materials and relevant portions of prior knowledge. The last two levels require learners to engage in higher quality thinking for understanding the presented materials and integrating past experiences into their learning process (Mayer, 2014). Due to the characteristics of MOOCs environment, learning processes can be analyzed through assessing the quality of learners’ thinking process expressed in online discussions (Smalbergher, 2017).

Besides Mayer’s model (Mayer, 2014), other scholars also developed frameworks that distinguished the quality of thinking into several levels. First, the revised taxonomy of Bloom (Krathwohl, 2002) divides cognitive domains into six hierarchical levels based on their complexity and abstraction. In this taxonomy, cognitive skills such as analysing, evaluating, and creating are classified as higher-order thinking skills, in contrast to lower-order skills which consist of remembering, understanding, and applying. Garrison, Anderson, and Archer (2001) also proposed a framework to analyse cognitive processes from written transcripts in a computer mediated communication. This framework sees higher-order thinking as a multi-phased process which started from triggering, exploration, integration, and resolution. In the framework by Marland, Patchin, and Putt (1992), thinking processes divided into six classes, namely evaluation, linking, strategy planning, generating, metacognition, and affective; while Herrington and Oliver (1999) classified higher-order thinking into six levels that consist of uncertainty, path of action, judgement, multiple perspectives, imposing meaning, and metacognition. Smalbergher (2017) integrated these frameworks to design the coding schema for identifying higher-order thinking in online discussions in MOOCs. More information about the schema and its relation with other higher-order thinking frameworks is discussed in the Instrument section (Chapter 3.4).

Higher-order thinking itself is an essential aspect in a learning process. Learners ability to use their higher-order thinking skills in a learning activity enables them to experience a deeper learning experience which is more meaningful and effective than surface learning where learners' merely use lower level cognitive functions such as simple memorization (Craik & Lockhart, 1972; Cui, Li, & Song, 2014). As a result, learners' higher-order cognitive efforts in learning were related with higher learning gains (Leflay & Groves, 2013; Wang et al., 2016). Higher-order cognitive processes also indicate higher cognitive engagement (Leflay & Groves, 2013). Czerkawski (2014) similarly explained that deep learning promotes learners' active engagement in a learning environment which encourages them to continuously explore, reflect, and produce information to build complex knowledge structure. As cognitive engagement has been proven to be predictive of learners' retention in MOOCs (Wen et al., 2014), thus, it is expected that learners' higher-order thinking also contributes to lower potential of drop out in MOOCs.

2.2. Dropout and completion in MOOCs

Regardless of the vast number of participants, some studies reported that the completion rate of MOOCs tends to be very low. Jordan (2014) found that on average 6.5% of the students enrolled in MOOCs met the criteria for earning a certificate. In a later study, she collected data from 217 MOOCs and found that the average of completion rate in MOOCs is approximately 12.6% (Jordan, 2015). Alraimi et al. (2015) also cited a number of sources to conclude that less than 10% of students enrolled in a MOOC completed the course. Some scholars, on the other hand, reject completion rate as a measure for evaluation of MOOCs, because learners may have different motivation and personal goals in learning in MOOCs (Liyanagunawardena, Parslow, & Williams, 2014; Stracke, 2017). Still, from the perspective of MOOCs providers, low completion rates seem to be an important issue (Bozkurt et al., 2017). Futurelearn, for example, stated that they demand the rates of full participation that they define as completing the majority of steps in a course including the assessments, although not treating it as the only measure of success (Nelson, 2018).

Several factors have been suggested as predictors of drop out in MOOCs, such as lack of motivation, lack of learning and digital skills, lack of time, as well as lack of support (Onah, Sinclair, & Boyat, 2014). Hew (2014), diversely, conducted a case study of three top-rated MOOCs and reported that five factors promote students engagement, including problem-centric learning, instructor accessibility, active learning, peer interaction, and helpful resources. The findings also suggested that, besides behavioural, motivational, and social factors, learners' cognitive aspects also contributed to their engagement in MOOCs. This is similar with

Czerkawski (2014) who explained that a deeper learning experience which involves higher-order cognitive processes promotes active engagement, thus, learners are encouraged to continuously explore the materials. However, how these factors influence learners' attrition has not been widely explored yet, therefore, it is interesting to specifically investigate how higher-order thinking processes impact learners' engagement in MOOCs.

2.3. Discussions in MOOCs

Online discussion is one of the most common features in an online learning environment which enables learners to interact and maintain discussions with peers or instructors related to their learning process at any time (Cobo et al., 2011). It enables learners to discuss, pose questions, receive and give answers, as well as express their opinions and feelings. For instructors, online discussions were also perceived as the most useful tool to monitor learners' activity and the course dynamics (Stephens-Martinez, Hearst, & Fox, 2014).

Literature suggested that online discussions have been found to promote learners' retention. As previously discussed that peer interaction and teachers accessibility are among factors that contribute to engagement (Hew, 2014), such interaction and access can be facilitated through an online discussion. Similarly, Swinnerton, Hotchkiss, and Morris (2017) also reported the results of numerous studies which found that learners who participated in online discussions are less likely to dropout than those who did not. In their study on nine MOOCs hosted in Futurelearn, they found that 'superposters', learners who post frequently and make tens to hundreds of comments, tend to 100% complete the courses, although not all learners who complete all of the MOOC were making a lot of comments.

Another benefit of online discussion is its capability to facilitate knowledge acquisition and higher-order thinking processes (Garrison et al., 2000; McLoughlin & Mynard, 2009; Wang et al., 2016). This is due to the asynchronous nature of the medium which provides learners with time to reflect and then contribute to the discussions with their formulated thoughts (Garrison et al., 2000). Garrison et al. (2000) also argued that cognition cannot be separated from the social context; therefore, collaboration –which usually happens through interaction in an online discussion, is also important in knowledge construction.

These factors of online discussions make identifying learners' thinking and knowledge construction processes possible through analysing learners' posts. However, such study is still scarce considering the characteristics of textual data in MOOCs online discussions which is large-scaled and less-structured (Wang et al., 2016), thus, difficult to analyse. For this, we employ text analysis and machine learning technologies to automate the analysis process.

2.4. Previous study

Smalbergher (2017) constructed a coding schema for identifying learners' higher-thinking process in an online discussion. The framework, following Mayer's SOI model (Mayer, 2014), distinguishes the quality of thinking into three levels in which the higher levels builds upon the levels below.

A supervised text classification tool written in Python with SVC classifier then was used to investigate the extent to which the identification of higher-order thinking process in online discussions can be automated. The final results show that the program can classify learners' comments into three different levels of thinking with 67% accuracy, whereas the binary classification can distinguish lower and higher-order thinking with 85% accuracy. The study showed that higher-order thinking process can be identified by the words that learners posted in online discussions. This is consistent with Tausczik and Pennebaker's (2009) postulation that the words which people choose might reflect the various depth and complexity of one's thoughts.

Smalbergher's study (2017), therefore, can be a basis for conducting a follow up research by applying the coding schema into different scripting language and different MOOC. Furthermore, the current study also investigates the relation between higher-order thinking and dropout, which, although important, was not addressed in the previous study.

2.5. Research questions

The study aims to explore learners' higher-order thinking processes from online discussions in a MOOC and investigate how learners' quality of thinking in the online discussions predicts learners' attrition in the MOOC. The research questions are formulated as follows.

1. **To what extent can the identification of higher-order thinking processes in online discussions of a MOOC can be automated?**

This research question will be answered through answering the following sub-questions:

1.1. To what extent can the program identify three different levels of higher-order thinking processes?

1.2. To what extent can the program make a distinction between lower and higher-order thinking in online discussions of a MOOC?

To answer this research question, a text classifier script was written in R. The program then will be used to classify all the learners' comments from the whole dataset. As it is also interesting to find out the impact of higher-order thinking processes in the online discussion towards attrition patterns in the MOOC, the study will also try to answer the following research question.

2. **How do learners' higher-order thinking processes in the online discussion impact attrition in the MOOC?**

As research about higher-order thinking process and its impacts on attrition in MOOCs is still scarce, it will be interesting to investigate the correlation of these two variables.

3. Methodology

3.1. Research design

The main goal of the study is to explore the potential to automatically identify and investigate the impact of higher-order thinking processes from learners' comments in online discussions. As such an objective is still relatively new and has not very explored, this study then requires an exploratory design.

This research is based on the mixed-methods approach, combining both qualitative and quantitative techniques. A qualitative data analysis through manual coding was performed to a number of sample comments based on the coding schema. Automated techniques also used to apply the classification model into the whole dataset. Furthermore, a quantitative data analysis was employed to see whether the quality of thinking can predict learners' attrition.

3.2. Participants and data collection

The study was conducted to a MOOC entitled "eHealth: Combining Psychology, Technology, and Health" provided by the University of Twente and hosted in Futurelearn. The total number of users who were enrolled within the six runs of the course was 3,343 learners. Futurelearn classified these users as Joiners (Nelson, 2018). However, the participants of this study were limited to users who are classified by Futurelearn as active learners or those who actually visit the course and mark at least one step as complete (Nelson, 2018). Therefore, the total number of participants was 2,582 learners with 25,721 discussion posts.

The participants were 135 female, 103 male, and 2,343 did not fill in their gender information. 1 participant were under 18 years old, 19 participants were between 18-25 years old, 39 participants were between 26-35 years old, 36 participants were between 36-45 years old, 52 participants were between 46-55 years old, 50 participants were between 56-65 years old, 33 participants were above 65 years old, while 2,351 users did not fill in their age information. Based on their highest education level, 1 participants finished below secondary education, 21 participants were secondary/high school graduates, 15 participants finished tertiary/post-secondary education, 90 participants were university/bachelor graduates, 71 participants finished their university master's degrees, 19 participants have university doctorate, 22 participants finished professional degrees, while 2,342 participants did not fill in the information about their highest education.

On the other hand, based on their employment area, 77 participants work in the field of health and social care, 35 participants work in teaching and education area, 22 participants work in IT and information services, 82 users are from other business sectors, while 2,365 participants did not fill in their employment information.

The data was automatically collected by the Futurelearn platform during the course while learners registered, voluntarily posted comments as a part of the course activities, and completed each step of the course. The data supplied is completely anonymous. Futurelearn users are informed that the data collected on the platform may be used for research purposes. This study was also conducted in accordance with the Futurelearn Research Ethics (Futurelearn, 2018).

3.3. The Futurelearn platform and datasets

Futurelearn is a MOOCs provider based in UK that was launched in 2013 by The Open University. The Futurelearn platform employs a social-constructivist pedagogy approach based on the Laurillard's Conversational Framework which postulates that an interaction must exist between the learner and the others for an effective learning process (Ferguson & Clow, 2015; Swinnerton et al., 2017). This implies the design of Futurelearn platform environment which provides easier access for learners to commenting, responding, and reflecting on the course materials.

Futurelearn courses are structured in weeks and the series of steps associated with each week. There are different types of learning materials in the Futurelearn platform, including article, video, discussion, quiz, test, and peer-assessment. Additionally, Futurelearn has its own design that prompts online discussions alongside the content. The online discussions are attached to each stage of learning, thus enable discussion in context and overcome the problems of lack of focus and off-topic comments in MOOCs discussions (Chua, Tagg, Sharples, & Rienties, 2017, Swinnerton et al., 2017). This approach posits that learners adapt their initial understanding and expand their knowledge within an iterative process by interaction with content, activities, educators, and peers, as well as reflective conversations within learners themselves during the process (Chua et al., 2017). With such a characteristic, it is possible to investigate which step/content that triggers more and higher-quality discussions.

Futurelearn also provides a set of data generated from the system from course start up until two weeks after it ends which covers daily activities within the course. There are twelve datasets provided, i.e., archetype_survey_response, campaigns, comments, enrolments, leaving_survey_responses, peer_review_assignments, peer_review_reviews, question_response, step_activity, team_members, and video_stats. This study only uses three datasets, namely 1) comments dataset which contains learners' discussion posts on the course, 2) enrolments dataset that contains information about participants' demographic information and roles within the course, and 3) step_activity dataset which contains information about learners' completion of every step in the course.

3.4. Instrumentation

To identify learners' higher-order thinking, textual data from learners' comments will be classified into three different levels of thinking using a schema developed by Smalbergher (2017), in which the higher level of thinking is built on its lower level. More specific indicators are depicted in Table 1.

Level 1 (taking new information) represents the lowest level of thinking. This level of thinking informs that a learner is engaged in a cognitive process of taking new information. This level is also in line with Remembering skill in Bloom taxonomy (Krathwohl, 2002) and

Triggering phase in COI cognitive presence framework (Garrison et al., 2001). Indicators for this level also include short length of the post and the comment does not contain any keywords that represent complex mental efforts.

Level 2 (interrelate and/or rearrange new information) indicates that a learner is in the process of connecting the information into a coherent structure. This process needs the Level 1 of thinking to happen beforehand as the process of interrelating information requires the process of taking new information. This level contains indicators from the Integration phase in cognitive presence framework (Garrison et al., 2001); Understanding and Analysing cognitive skills in Bloom taxonomy (Krathwohl, 2002); Evaluation, Linking, and Generation in Marland et al. (1992); as well as Judgement & interpretation, Multiple perspectives, and Imposing meaning in Herrington and Oliver (1999). Comments belong to this category is usually medium or long in length and contains specific keywords that represent higher mental effort.

Level 3 (extending the use of new information into existing knowledge to achieve a purpose), represents learners' ability in making sense the new information with their prior knowledge and apply the learned information to solve a different problem in their own context. The indicators of this level are also found in other frameworks such as Evaluating and Creating skills in Bloom (Krathwohl, 2002); Resolution phase in COI cognitive presence framework; Metacognition in Marland et al. (1992); as well as Self-regulation of thinking in Herrington and Oliver (1999). As for integrating new information into prior knowledge and applying it in a new context requires the interrelation of the new information as indicated in Level 2, comments in this level can also be identified with keywords in Level 2. Furthermore, personal pronouns and keywords that indicate experience (past tense) are also used.

Table 1 summarizes the indicators of each level along with its alignment with indicators from other higher-order thinking frameworks and its respective keywords and rules.

Table 1

The coding schema (Smalbergher, 2017)

Mayer's SOI model	Levels of the higher-order thinking process	Bloom	Garrison	Marland	Herrington	Keywords and other rules
Selecting "focusing attention on relevant pieces of information"	**Level 1** "Taking new information"	**Remember** "recall relevant information without engaging in a cognitive process of understanding"	**Triggering** "the correct identification of the problem that is discussed, students having a "sense of puzzlement" towards the subject"	n.a.	n.a.	- short length of the comment - no KW from L2 and L3
Organising "forming a coherent structure from the construction of internal connections between selected information"	**Level 2** "interrelate and/or rearrange the new information"	**Understand** "constructing meaning of the new information" **Analyze** "understanding the structure of something, making inferences, searching for evidence and explanations"	**Integration** "connecting ideas and synthesizing information and constructing meaning"	**Evaluation** "judgement towards concepts" **Linking** "synthesizing or connecting concepts, experience, and ideas" **Generating** "reasoning, making prediction, or elaborating"	**Judgement & Interpretation** "defending an issue or opinion, making connections, and giving definitions" **Multiple perspectives** "seeing both parts of an issue, challenging different ideas, and giving alternatives" **Imposing meaning** "synthesizing information, giving conclusions, presenting believes, and alternative solutions"	- Medium – long length of the comment - Because - However - If – then - So - Hence - As - Though - Whereas - On one hand – on the other hand - Whereby - As long as - Unless - Effect - Cause - Know - Ought - In order to - Rather than
Integrating "relating the new knowledge to the existing information"	**Level 3** "Extend the use of the new information to existing knowledge or past experiences to achieve a purpose or find possible answers"	**Evaluate** "judging the new information by comparing it with information from past experiences" **Create** "combines ideas from prior knowledge to form new ideas or products into a new structure or product"	**Resolution** "defending the solutions, found or giving argumentation and reasoning based on real world experiences"	**Metacognition** "aware of their thinking processes and self-directing their thinking through reflections or evaluations"	**Self-regulation of thinking** "awareness of their thinking processes and understandings"	- Long length of the comment - Past tense - KW from L.2 + - I - My - Experience

3.5. Procedure and data analysis

This study used two different data analysis methods to answer the research questions. Text classification method was used to analyze learners' comments and identify its quality, whereas survival analysis was used to quantify the effect of higher-order thinking process towards the learners' retention in the MOOC.

3.5.1. Text classification

Text mining, or text analysis, refers to the process of extracting non-trivial information and knowledge from unstructured text (Moreno and Redondo, 2016). It uses techniques from multidisciplinary fields, such as information extraction, data mining, machine learning, statistics, and computational linguistics, resulting in structured or semi-structured information to be further used (Moreno and Redondo, 2016). Text mining can be used to analyze discussions in MOOCs due to the nature of textual data which is large-scaled, less-structured, but contains a large amount of information about student's engagement with the course (Wang et al., 2016).

In this study, text mining was used to classify comments into several pre-defined categories, which is also known as supervised text classification approach. In supervised text classification approach, the classifier tool needs to be trained using annotated sample dataset to recognize the features and extract the class label. For this end, a manual analysis needs to be performed to construct the training dataset.

Data preparation

Before applying the data mining and analysis technique, it is important to make sure that the dataset is of a good quality. First, datasets from six different offerings of the course were combined, resulting in three datasets: comments, step_activity, and participants; containing the whole data from six runs of the course. Data belongs to instructors and course administrators were removed. Rows containing empty data and malformed data due to character encoding issues were also deleted. Then, for the manual coding purpose, the comment dataset was randomized and the top 2,038 comments were selected as a sample dataset that will be manually analysed and used to train the classifier.

Manual coding

The training dataset was constructed by manually analysing the comments and rating each post level 1, level 2, or level 3 according to Smalbergher's coding schema (2017). The process was done by two coders who are master's students in Educational Science program and Psychology program. First, both coders sat together, discussing the indicators of the coding schema. Then, the coders worked together on the same data (100 data). The result of Cohen's kappa calculation shows that the data have a very high inter-rater reliability with the score of 0.85. Another discussion took place to compare and validate the data. Then, the rest of 1,938 data were divided among the coders to be manually analysed. Table 2 provides the samples of the coding data.

Table 2
Samples of coding data

Comment	Level of thinking
Very well presented introduction. I have an open mind.	Level 1
There should be a flow chart with pertinent questions. A microbiologist would then give examples of appropriate treatments. This could be electronic and questions show according to answers. Need to include past use of antibiotic	Level 2
There are so many current and potential possibilities for eHealth to have a positive benefit for us. I use some great (highly sophisticated) apps for fitness and activity monitoring now - I would like to know why it seems so difficult to apply this sort of technology in other areas of healthcare. I work in dentistry and believe that giving patients a better connection with their clinicians through eHealth will help improve their personal dental care. I would like to have a better understanding of how to do this by the end of the course. I'm also currently studying for an MBA in Healthcare and it is important for me to have greater in-depth knowledge about this growing phenomenon.	Level 3

Feature selection

The annotated sample dataset was split into training group and testing group with the proportion of 70% and 30% respectively. Proportional random sampling was used to keep the proportion of classes similar to the whole sample dataset.

Table 3
The proportion of train and test group from the annotated sample dataset

	Train		**Test**	
	N	**%**	**n**	**%**
Level 1	439	30.76%	188	30.77%
Level 2	507	35.53%	217	35.52%
Level 3	481	33.71%	206	33.71%
Total	1427		611	

The annotated training dataset was then observed to get a deeper insight into its characteristics. From this observation, we decided to include several features into the pipeline. Length of the text was included after being transformed into three categories: short (less than or equal to 160 characters), medium (between 160 and 480 characters), and long (more than or equal to 481 characters). N-grams (unigrams, bigrams, and trigrams) were extracted from the corpus and sparse terms were removed. Features that might not indicate higher-order cognitive efforts such as URL, numbers, symbols, and some stop words were also removed.

Classifier implementation

The feature sets then inputted into four different classification algorithms – RPart (recursive partitioning), SVM (supervised vector machine), Naïve Bayes classifier, and KNN (K-nearest neighbors) and trained under 10-fold cross-validation. During the training process, the classifier collects the most distinctive features from the sample dataset and determines the relationship between the features and the class label. The best performing algorithm in identifying the data was chosen and validated by predicting the data in the testing data group.

Binary classification

To find out the extent to which the classifier can distinguish lower-order thinking and higher-order thinking processes from online discussion posts, the manually coded dataset needs to be adjusted. Level 1 of thinking then changed into 0, representing that the learner did not engage in a higher-order cognitive effort, in contrast with Level 2 and Level 3 that were merged into 1 that represents engagement in a higher-order thinking process.

The dataset then randomly split into train (70%) and test (30%) datasets using proportional random sampling technique to keep the proportion of classes in the train and test datasets similar with that of the sample dataset. Table 3 depicts the proportion of sample data for the binary classification.

Table 3.
The proportion of train and test group for the binary classification

	Train		Test	
	N	**%**	**n**	**%**
Lower-order thinking	439	30.76%	188	30.77%
Higher-order thinking	988	69.24%	423	69.23%
Total	1,427		611	

Similar feature extraction and classifier implementation methods were carried out. Next, the classification model was applied to the remaining data in the comments dataset. As a result, every post in the comments dataset was labelled with its representing level.

3.5.2. Survival analysis

Survival analysis was performed to estimate the impact of higher-order thinking towards attrition. Ameri, Fard, Chinnam, and Reddy (2016) defined survival analysis as "… a collection of statistical methods which contains time of a particular event of interest as the outcome variable to be estimated" (p. 905). Compared to logistic regression, survival analysis has an advantage in investigating student retention problem as student retention is a lengthy process that depends on time (Ameri et al., 2016). Therefore, survival analysis can provide information regarding when the dropout exactly happens, in addition to which learners are most likely to dropout.

In this study, we used four variables (see Table 4) for the survival analysis. The dependant variable is attrition, which is represented as a binary indicator that indicates whether a learner completed the course or not. On the other hand, learners' higher-order thinking is used as the independent variable. This refers to a binary indicator that describes whether or not a learner ever posted a comment that indicates higher-order thinking which is represented by value 1 from the result of the binary classification process.

Several research suggested that learners who participated in online discussions were have higher possibility to complete the MOOCs (Swinnerton et al., 2017). We, therefore, employed forum participation as the control variable which indicates whether a learner ever posted a comment in the discussion. Furthermore, as survival analysis requires a time variable, we used the steps in the MOOC, started from Week 1 Step 1 (1.1) to Week 6 Step 20 (6.20), as the time scale (see Appendix A for the description of each step in the course). This enables to find out an information regarding which specific steps and weeks of the course that the learners more likely to dropout.

Table 4.
Variables

Dependent variable	attrition	A binary indicator that indicates a learner completed a step
Control variable	forum_participation	A binary indicator that describes whether a learner ever posted a comment in the discussion
Independent variable	higher_order_thinking	A binary indicator that describes whether a learner ever posted a comment that indicates higher-order thinking processes
Time variable	steps	The steps (contents) of the course, started from Week 1 Step 1 (1.1) to Week 6 Step 20 (6.20)

To calculate the effects of higher order thinking and forum participation towards attrition, a Cox proportional hazard model is structured. In contrast with multiple and logistic regressions that give odds ratios, The Cox model generates hazard ratios (HR) for the measure of effect (Kleinbaum & Klein, 2012). However, both measures have similar interpretation of the strength of the effect. For example, a hazard ratio of 1 means that there is no effect, while the hazard ratio of 2 means that a group has twice probability to drop out than a comparison group.

4. Results

4.1. Automated text-classification tool

The first research question of this study focused on investigating the extent to which higher-order thinking processes can be automatically identified from the online discussions in MOOC. To answer this question, a supervised text classification model was determined using R programming language. Furthermore, two sub-goals were also formulated: 1) to what extent the program can identify three levels of higher-order thinking processes from online discussions; and 2) to what extent the program can distinguish between lower-order thinking and higher-order thinking from online discussions.

4.1.1. Multiclass classification

The training data was inputted into the selected features. Then, machine-learning algorithms were trained to identify three levels of thinking from learners' comments. The performance results for the models are presented in Table 5.

Table 5.
Multiclass classifier performance results on train data group

Classifier	Accuracy			Kappa		
	Min	Mean	Max	Min	Mean	Max
RPart	0.57	0.67	0.74	0.35	0.50	0.61
SVM	0.62	0.72	0.81	0.43	0.58	0.72
Naïve-bayes	0.48	0.56	0.65	0.24	0.35	0.48
K-NN	0.30	0.31	0.32	- 0.01	0.002	0.02

The table shows the performance of the classifying algorithms the classification models constructed using the training. It is shown that SVM performed best with 62% accuracy and kappa of 0.58.

We ran a chi-square test to get the Cramer's V value that measures the strength of association between each feature and its representative label. Among 222 features, 30 most important features are depicted in Table 6.

Table 6.
The most important features per-class

Feature	V	Feature counts		
		Level 1	Level 2	Level 3
TextLength	0.5815185	-	-	-
if	0.3652137	18	172	209
as	0.3598756	25	136	218
I	0.3590906	147	236	369

have	0.3520988	34	124	223
can	0.3034894	40	165	205
they	0.2989744	14	65	143
would	0.2861580	24	120	167
but	0.2843690	33	93	173
because	0.2752190	5	52	111
also	0.2730321	10	94	131
when	0.2669776	3	45	100
from	0.2664798	12	74	127
there	0.2647586	13	88	131
my	0.2640497	58	56	164
people	0.2593023	19	80	136
me	0.2582553	18	22	98
who	0.2468344	7	35	91
their	0.2457919	10	73	112
will	0.2436849	20	120	127
in the	0.2416706	31	79	143
think	0.2384650	15	98	118
dont	0.2384650	5	21	73
could	0.2342625	13	108	104
some	0.2336440	13	55	105
i think	0.2329169	7	81	98
time	0.2297789	10	74	103
we	0.2282800	19	40	102
so	0.2182322	68	171	190
see	0.2172412	9	47	88

The model then was validated to the test data group containing 611 numbers of data. Confusion matrix depicted in Table 7 shows how the SVM classifier identified the level of thinking from each comment. The model correctly predicted 160 out of 188 comments in the Level 1 category, 132 out of 217 comments in the Level 2 category, and 152 out of 206 comments in the Level 3 category.

Table 7.

Confusion matrix of the multi-class classification on test data group

	Actual			
Predicted	**Level 1**	**Level 2**	**Level 3**	**Row total**
Level 1	154	39	15	208
Level 2	23	143	59	225
Level 3	9	44	124	177
Column total	186	226	198	611

Although the Kappa value (0.58) is considered acceptable according to Fleiss and Cohen (as cited in Rosé et al., 2008) which is at least 0.4, however, this number is substantially lower than 0.8 or at least 0.7 as suggested by Krippendorff (as cited in Rosé et al., 2008). In this study, we are strict with Krippendorff's recommendation to ensure the quality of the classifier.

4.1.2. Binary classification

Binary classification was performed to find out the extent to which the classifier can distinguish between lower-order thinking and higher-order thinking processes from online discussion posts. The features in the binary training data group was inputted into the classifier model and the machine learning algorithms were trained to distinguish between comments with lower-order thinking and those with higher-order thinking. The classifier performances were depicted in Table 8.

Table 8.
Binary classifier performance results

	Accuracy			Kappa		
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**
RPart	0.82	0.89	0.94	0.57	0.73	0.86
SVM	0.85	0.90	0.95	0.65	0.78	0.89
Naïve-bayes	0.57	0.64	0.73	0.27	0.36	0.50
K-NN	0.31	0.34	0.37	0.00	0.03	0.06

As shown in the table, SVM outperformed the other classification algorithms. For the binary classification task, the classifier was able to achieve 90% accuracy with the kappa of .78 which shows a moderate level of agreement.

A chi-square test then was carried out to find out the importance of the features towards the prediction. Among 206 informative features, the 30 most informative features are presented in Table 9.

Table 9.
The most informative features per class for binary classification

		Feature counts	
Feature	**V**	**Lower-order thinking**	**Higher-order thinking**
TextLength	0.724104054	-	-
if	0.350537731	18	189
as	0.322085409	22	353
can	0.268884294	46	364
but	0.261524059	23	281
think	0.259136739	10	230
would	0.258623949	22	274

I	0.254816394	141	590
also	0.252308567	15	241
could	0.250067704	10	219
have	0.243765479	42	322
i think	0.24336595	4	186
will	0.236818209	20	241
they	0.228079806	12	201
there	0.227645443	15	212
their	0.217472714	9	177
people	0.217151214	21	222
time	0.213881051	11	181
when	0.213604447	3	147
so	0.212274025	70	367
because	0.210107579	5	152
all	0.207173016	15	189
from	0.207083343	18	200
in the	0.197540721	30	231
has	0.191762913	12	261
should	0.19049624	5	131
patient	0.189735729	9	147
which	0.18792763	12	157
can be	0.18115057	7	130
them	0.180013212	8	133

The model was validated to the test data group containing 611 numbers of data. Confusion matrix depicted in Table 10 shows how the SVM classifier distinguished lower-order and higher-order thinking from learners' posts. The model correctly predicted 161 out of 188 comments in the lower-order thinking category and 380 out of 423 comments in the higher-order thinking category.

Table 10.
Confusion matrix of the multi-class classification on test data group

	Actual		
Predicted	**Higher-order thinking**	**Lower-order thinking**	**Row total**
Higher-order thinking	161	43	204
Lower-order thinking	27	380	407
Column total	188	423	611

As the results show that the model can predict learners' comments better with a moderate level of agreement (Kappa 0.78), the model can be implemented to automate the coding of learners' posts. The model then was applied to the rest of the comments dataset in order to automatically identify the level of thinking from each comment. Of the total comments in the MOOC, 12,358 and 13,362 were identified as lower order and higher-order thinking respectively.

4.2. Survival analysis

We apply survival analysis to investigate whether learners' higher-order thinking correlates with dropout from the MOOC.

4.2.1. Overall retention pattern

Figure 1 shows the Kaplan-Meier curve that illustrates the cumulative proportion of learners who did not come back to the course at a certain step of the course. The data show that only 14.49% (374) of learners completed the course. The graph also shows that learners tended to drop out early than later, where more than a half of learners left the course at Week 1 while only 48.2% of learners completed the first week and continued to Week 2.

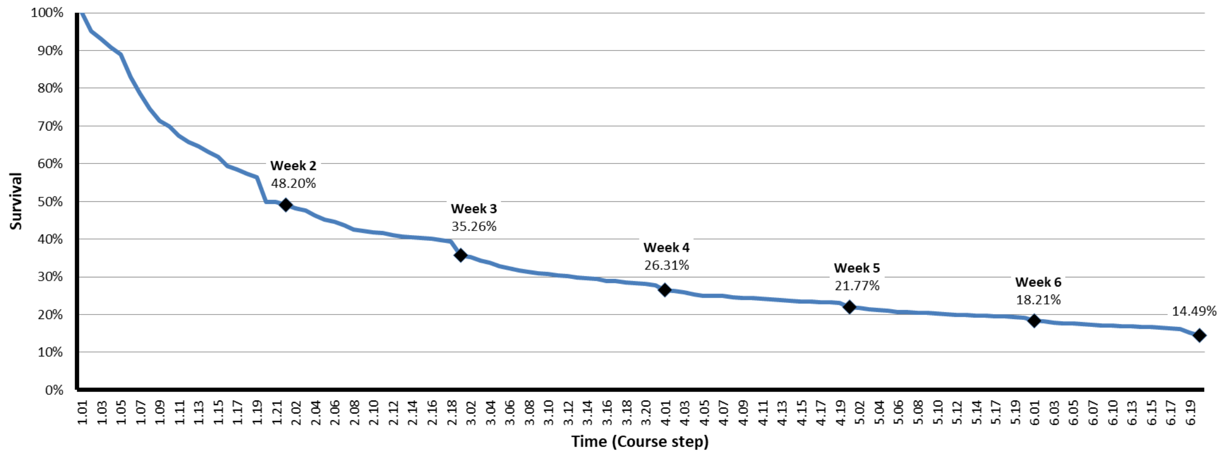

Figure 1. Kaplan-Meier curve for the pattern of drop out in the course

Additionally, Table 11 describes 10 course steps with the highest number of dropouts. Appendix B contains the complete results of survival analysis for the whole course.

Table 11.
10 steps with the highest number of dropouts

No.	Step	Content type	% dropout
1.	1.19	Article	11.74%
2.	2.18	Article	9.07%
3.	1.05	Quiz	6.70%
4.	1.06	Article	5.32%
5.	6.19	Discussion	5.32%
6.	1.07	Article	5.17%
7.	6.18	Test	5.05%
8.	1.01	Video	4.88%
9.	3.21	Discussion	4.73%
10.	4.19	Article	4.54%

4.2.2. Retention patterns for forum participation and higher-order thinking process

Figure 2 illustrates the difference between learners who participated in the online discussion by posting at least one comment and those who did not. The blue curve shows the survival of learners who have posted, while the orange curve displays the survival of learners who did not post. In general, comment posters stayed longer than the non-commenters group, with 17.76% of those who participated in the discussion completed the course, compared to 10.67% of learners who did not participate.

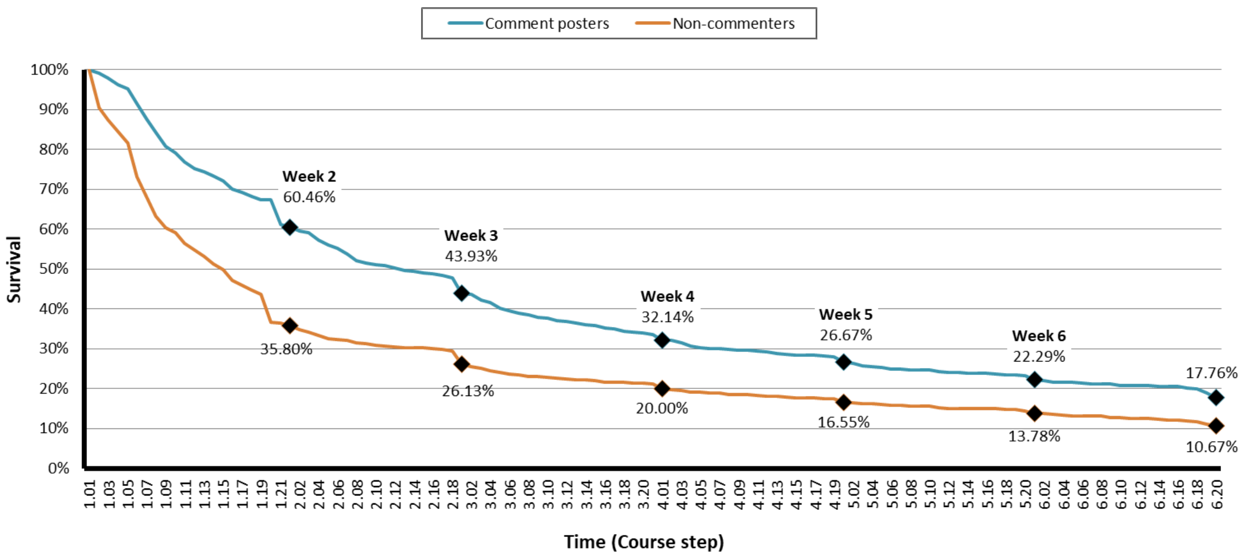

Figure 2. Kaplan-Meier curve for the effect of forum participation towards survival

Figure 3, on the other hand, depicts the retention pattern of learners who engaged in a higher-order thinking process by posting comments that have signs of higher-order cognitive efforts. The blue curve shows the survival pattern of learners' who demonstrated higher-order thinking, whereas the red curve represents the survival of learners' who only showed lower-order thinking. Participants who demonstrated higher-order thinking stayed longer in the course than those who only engaged in lower-order cognitive efforts with 20.03% and 7.26% respectively.

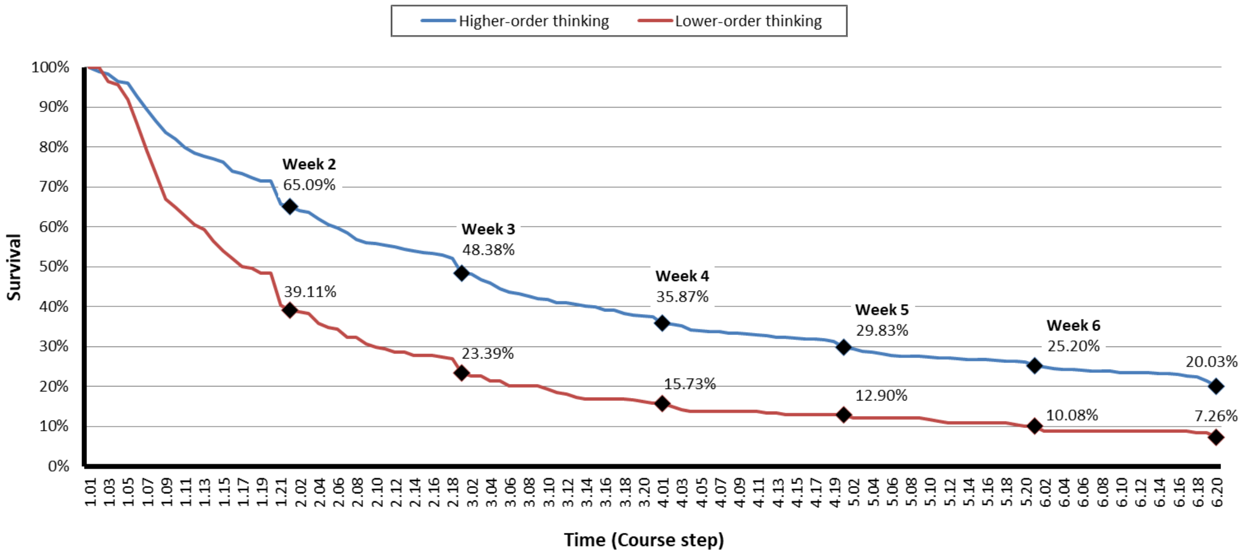

Figure 3. The effect of engaging in higher-order thinking towards survival

4.2.3. Cox proportion hazards calculation

Table 12 reports the estimate of the survival analysis models for the control and independent variables that were analyzed using Cox proportional hazards. The effects are reported in Hazard ratio, which interpreted as the effect of an explanatory variable on the risk or probability of participants to drop out from the course.

Table 12

Cox proportional hazards calculation for each variable

Variables	**Hazard ratio**	**Probability to dropout**
forum_participation	1.4695	46.95%
higher_order_thinking	1.7568	75.68%

The hazard ratio value for the forum_participation variable means that the survival in the course was 46.95% higher for those who have participated in the online discussion by posting at least one comment. Controlling for learners' forum participation, higher_order_thinking significantly influenced the dropout rates in the same direction. Learners whose posts indicated engagement in higher-order cognitive efforts were 75.68% more likely to continue participating in the course compared to those who did not.

5. Discussions

5.1. Automated identification of higher-order thinking from online discussions

One of the focuses of the study is to investigate the extent to which the identification of higher-order thinking can be automated. Our findings suggest that higher-order thinking processes in the MOOC's online discussion can be automatically identified using a text classification program.

A supervised text classification model was determined in R, trained with manual coded datasets, and validated. The results demonstrated that the classifier was able to identify three levels of thinking through the words that the learners expressed in the online discussion. The multiclass classification achieved 62% accuracy and the agreement of 0.58 Cohen's kappa, while the binary classification was able to distinguished lower-order and higher-order thinking with 90% accuracy and the Cohen's kappa of 0.76. Although the multiclass classification achieved an acceptable level of agreement according to Fleiss and Cohen (as cited in Rosé et al., 2008), we were strict with Krippendorff's recommendation that suggested the Cohen's kappa to be at least 0.70 or 0.80 to make sure that the classification can handle the data from a large-scale, varied, and unstructured MOOCs discussions.

We also tested four classification algorithms, RPart (recursive partitioning), SVM (supervised vector machine), Naïve Bayes classifier, and KNN (K-nearest neighbors). It was found that SVM outperformed the other classifiers in both multiclass and binary classifications. This confirms the finding of Khan, Baharudin, Lee, and Khan (2010) which suggested that SVM classification method is more effective than other methods in text classification.

From the Chi-square test that was conducted to identify the most informative features, it was revealed that the length of the text that the participants write can be a strong predictor of higher-order thinking. This was addressed by Smalbergher (2017) in the coding schema; however, this feature was not included in her classifier model. The feature extraction also showed that from 30 most important features, 29 features were visible in the Level 3 class, 1 feature was visible in the Level 2 class, whereas no feature was visible in the Level 1 class for the multiclass classification. On the other hand, all of the 30 most important features were belongs to the category of higher-order thinking in the binary classification. The possible reason for this is because there were no specific criteria for the Level 1 class, while the criteria for Level 2 and Level 3 were less distinctive for a classifier to recognize.

Another reason is that the current text classification relies primarily on the appearance of keywords in the data. For example, the post *"I have never used e-health services, but if it is necessary I will use it"*, although containing words that indicate Level 2 and Level 3 of thinking according to the coding schema, it actually does not demonstrated that the author is engaging in a higher-order thinking by using her prior knowledge to judge the material or using the information in the material to her context. Still, such a kind of statement might be classified as Level 2 or Level 3 by the classifier. Conversely, the learner might be engaging in a higher-order thinking process but using different words that were not recognized by the machine as distinctive features. This causes the comment to be classified as Level 1 as the specific keywords for Level 1 was not specified in the classification program.

The results from the Chi-square test revealed that all of the 30 most informative features were function words instead of specific content words. Function words are defined as words that are used to express grammatical structure or mood of the speaker, in contrast with content words that convey the content of a communication (Tausczik & Pennebaker, 2009). This might be caused by the characteristics of the course that is very broad and contains 119 content pages (steps) as well as the number of training data that is quite big with 2,038 documents. As explained by Miller (as cited in Tausczik & Pennebaker, 2009) that function words make up about 55% of all the words that people use, the proportion of function words in the training dataset might be much higher compared to the content words, such as specific nouns. The classifier might recognize these function words and put them in the classifying model. On the other hand, the content words were considered by the classifier as sparse and insignificant, thus removed from the model. However, this is ideal for the generalizability of the classifier as the coding schema was designed to be implemented in various kinds of MOOCs (Smalbergher, 2017).

The results also show the relevance of Tausczik and Pennebaker (2009) postulation that certain words can be used to identify one's depth of thinking and cognitive complexity. These words include exclusive words (e.g., but, without, exclude), conjunctions (e.g., and, also, although), prepositions (e.g., to, with, above), causal words (e.g., because, effect, hence), insight words (e.g., think, know, consider), as well as tentative language (e.g., maybe, perhaps, guess).

It seems that the classification model designed in this study has higher accuracy than the tool used in the previous study by Smalbergher (2017). However, although this study shows that including the length of comments into the feature set and using more training data improved the classification performance; it does not imply that this classifier works better with different datasets. Considering that the classifier model is induced from the training dataset; therefore, the data should be carefully prepared by ensuring that the training data represents the whole data in the comments dataset. Furthermore, data exploration is also an important phase when selecting the features and developing the classifier as it gives insights into the data that we are working with.

Overall, while online discussions contain rich data about learners' thought and learning processes but difficult to analyse due to the characteristics of the data (Wang et al., 2016), the classification program demonstrates an acceptable performance to identify higher-order thinking processes from an online discussion. Therefore, the tool can be used to automate the analysis of learners' posts although more improvements are still required.

5.2. The impact of higher-order thinking towards retention in MOOCs

We attempted to find the impact of higher-order thinking towards attrition in MOOCs because, although low completion rates are still an issue in MOOCs (Alraimi et al., 2015; Bozkurt et al., 2017; Jordan, 2015), to our knowledge, there has not been any study that investigates the correlation between those two. Using survival analysis, we found that learners who engaged in higher-order thinking have a lower risk of drop out than those who did not.

As higher-order thinking is an indicator of learners' cognitive engagement (Leflay & Groves, 2013), the findings of the current study are relevant with those of Wen et al. (2014) which suggested that learners' cognitive engagement predicts their probability to complete the course. Furthermore, this study is also in line with Hew (2014) who found that one measure to promote engagement is by providing students with problem-centric and active learning and assessments that challenge learners' cognitively.

A possible reason is by engaging in a higher-order thinking process, learners are going beyond simple memorisation towards a deeper learning experience which utilizes more complex cognitive functions such as reflection, critical thinking, and problem solving (Cui et al., 2014). Moreover, as Czerkawski (2014) suggested that deep learning encourages learners to continuously explore, reflect, and produce information, learners who engage in a deeper learning experience would possibly stay longer and actively involved in the course.

Other studies also suggested that higher-order thinking correlates with higher learning gains (Leflay & Groves, 2013; Wang et al., 2014), which means that learners who demonstrate higher-order cognitive efforts learn more than those who only rely on their lower-order thinking. Additionally, as argued by Ke and Xie (2009), higher-order thinking during learning also facilitates higher-order knowledge acquisition. As a result, the content becomes more relevant and significant for them. This positive experience may have encouraged them to continue and complete the course.

On the other hand, we surprisingly found that participating in the discussion without engaging in higher-order thinking has a higher probability to drop out than not participating in the discussion at all. This is different with the existing literature which reported that participating in online discussion promotes engagement in MOOCs (Hew, 2014; Swinnerton et al., 2017). The possible reason for this is because we did not take the number of comments into account when calculating forum participation, thus, learners who post once was treated the same with learners who post more frequently. Some learners might only participated during the introduction section without engaging in a higher-order thinking process and dropped out in the next section. Furthermore, as we only measured the quality of thinking through the comments that the learners posted, we could not identify higher-order thinking process from learners who did not participate in the discussion, although we believe that higher-order thinking process also occurs in learners who did not participate in the discussion.

Despite the importance of cognitive processes in learning, the current techniques of assessments in MOOCs were not sufficient to facilitate and measure learners' higher-order thinking (Smalbergher, 2017; Spector, 2017; Yousef et al., 2016). Hew (2014), for example, reported that instructors in the courses that he studied relied mainly on peer assessment to engage learners cognitively. However, other study found that peer-assessment was linked to higher dropout rates (Onah et al., 2014). Therefore, our approach to automating assessments in MOOCs might also be beneficial in the future, as it enables course designers and instructors to implement active and problem-centric learning with minimal risk of drop out.

6. Conclusion, limitations, and future recommendations

As MOOCs are often criticised in terms of their quality to deliver a deeper learning experience, especially in the lack of learning and formative assessment methods that are able to engage and monitor learners' thinking and learning processes (Hew, 2014; Spector, 2017; Yousef et al., 2016), learners' posts in the online discussions provide a rich data about how the learners' think and learn in the course (Wang et al., 2016). Another important issue in MOOCs is the high drop out rates that still need further studies to identify the contributing factors and the possible measures to address the issue (Bozkurt et al., 2017). The aims of this exploratory study are investigating the extent to which higher-order thinking can be automatically identified from using a supervised text classification technique and examining the impact of learners' higher-order thinking towards retention in a MOOC.

We developed a text classification model to automatically identify the signs of higher-order thinking from learners' posts in the online discussion of a MOOC in accordance with the coding schema by Smalbergher (2017). The developed classifier for multiclass classification that was able to distinguish learners' quality of thinking into three levels achieved 62% accuracy and the agreement of 0.58 Cohen's kappa. On the other hand, our binary classifier was able to make a distinction between higher-order thinking and lower-order thinking with 90% accuracy and the Cohen's kappa of 0.76 which is considered an acceptable level of agreement (Rose, 2008). We then used survival analysis to compute the effects of learners' quality of thinking towards retention. The results revealed that learners' who engaged in higher-order thinking in the MOOC's discussion have lower risk to drop out compared to learners' who only engaged in lower-order thinking.

This result of this study provides a new insight regarding the relationship between learners' quality of thinking and attrition in MOOCs that has not been addressed in the existing literature. It also provides a basis to implement a learning analytics tool to monitor learners' quality of thinking in MOOCs as well as drop out early prediction system. Such monitoring tools can help instructors to understand learners better during the learning process and make decisions on proper interventions or provide more timely and effective feedback.

There were, however, several important limitations to the current study. First, the classifier model used in this study relies primarily on the appearance of keywords in the data. The model might be unable to correctly identify a post if the author uses different words with those of in the training datasets. Including more features such as number of likes and replies, as well as employing more advanced text analysis and natural language processing techniques such as coh-metrix that measure the cohesion and coherence of a text will probably improve the accuracy. Second, this study did not take the number of posts into account when calculating the forum participation and higher-order thinking during the survival analysis; therefore, learners who post once was treated the same with learners who post more frequently. It is recommended to calculate the number of posts as there will be differences between learners who post more comments and those who post fewer (Swinnerton et al., 2017). Finally, this study only focused to investigate the quality of thinking from learners who posted comments, while there might be learners who participate only by reading the discussion yet still engage in higher-order thinking processes.

Future research should also focus on improving the accuracy of the classifier by adding and testing more features, not limited only to discussion features, such as number of logins, average time spent per-session, number of pauses during the video, as well as quiz results. It is also recommended to train the classifier model with more data from more than one different courses. Furthermore, although this study revealed that there is a relationship between higher-order thinking and attrition, there is no clear explanation why this happens. It is, therefore, recommended to use surveys or interviews with learners to investigate why learners choose to stay or leave the course.

References

Abeer, W., & Miri, B. (2014). Students' preferences and views about learning in a MOOC. *Procedia -Social and Behavioral Sciences, 152,* 318-323. DOI: 10.1016/ j.sbspro.2014.09.203

Allen, I. E., & Seaman, J. (2016). *Online report card: Tracking online education in the United States.* Babson Park, MA: Babson Survey Research Group and Quahog Research Group. Retrieved from http://onlinelearningsurvey.com/reports/onlinereportcard.pdf.

Alraimi, K. M., Zo, H., Ciganek, A. P. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers & Education, 80,* 28-38. DOI: 10.1016/ j.compedu.2014.08.006

Ameri, S., Fard, M. J., Chinnam, R. B., Reddy, C. K. (2016). Survival analysis based framework for early prediction of student dropouts. *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management* (pp. 903-912).

Bozkurt, A., Akgün-Özbek, E., Zawacki-Richter, O. (2017). Trends and patterns in massive open online courses: review and content analysis of research on MOOCs (2008-2015). *International Review of Research in Open and Distributed Learning, 18(5),* 118-146. DOI: 10.19173/irrodl.v18i5.3080

Brookhart, S. M. (2010). *How to assess higher-order thinking skills in your classroom.* Alexandria, VA: ASCD.

Chua, S. M., Tagg, C., Sharples, M., Rienties, B. (2017). Discussion analytics: Identifying conversations and social learners in Futurelearn MOOCs. In L. Vigenti, Y. Wang, L. Paquette. M.L. Urrutia (Eds.), *MOOC analytics: live dashboards, post-hoc analytics and the long-term effects. Joint MOOCs workshops from the Learning analytics and Knowledge (LAK) Conference 2017, Vancouver, Canada on March 13-17, 2017*. (pp. 36-62).

Cobo, G., García, D., Santamaría, E., Morán, J. A., Melenchón, J., Monzo, C. (2011). Modeling students' activity in online discussion forums: A strategy based on time series and agglomerative hierarchical clustering. *Proceedings of the 4th International Conference on Educational Data Mining, Eindhoven, The Netherlands* (pp. 253-258).

Craik, F. I. M., Lockhart, R. S. (1972). Levels of processing: A framework for memory research. *Journal of Verbal Learning and Verbal Behavior, 11(6),* 671-684. DOI: 10.1016/S0022-5371(72)80001-X

Cui, L., Li, H., Song, Q. (2014). Developing the ability for a deep approach to learning by students with the assistance of MOOCs. *World Transactions on Engineering and Technology Education, 12(4),* 685-689.

Czerkawski, B. (2014). Designing deeper learning experiences for online instruction. *Journal of Interactive Online Learning, 13(2),* 29–40.

Dillahunt, T., Wang, Z, Teasley, S. D. (2014). Democratizing higher education: exploring MOOC use among those who cannot afford a formal education. *The International Review of Research in Open and Distributed Learning, 15(5),* 177-196.

Ferguson, R., Clow, D. (2015). Examining engagement: analysing learner subpopulations in massive open online courses (MOOCs). *Proceedings of the 5th International learning analytics and knowledge Conference (LAK15), 16–20 March 2015, ACM, Poughkeepsie, NY, USA* (pp. 51-58). DOI: 10.1145/2723576.2723606

Friedman, T. L. (2012, May 16). Come the revolution. *The New York Times.* Retrieved from http://www.nytimes.com/2012/05/16/opinion/friedman-come-the-revolution.html

Futurelearn (2018). *Research ethics.* Retrieved from: https://about.futurelearn.com/terms/research-ethics-for-futurelearn

Garrison, D. R., Anderson, T., Archer, W. (2000). Critical inquiry in a text-based environment: computer conferencing in higher education. *The Internet and Higher Education, 2 (2–3),* 87-105.

Garrison, D. R., Anderson, T., Archer, W. (2001). Critical thinking, cognitive presence, and computer conferencing in distance education. *American Journal of Distance Education, 15(1),* 7-23. DOI: 10.1080/08923640109527071

Herrington, J., & Oliver, R. (1999). Using situated learning and multimedia to investigate higher-order thinking. *Journal of Interactive Learning Research, 10(1),* 3-24.

Hew, K. F. (2014). Promoting engagement in online courses: What strategies can we learn from three highly rated MOOCs. *British Journal of Educational Technology, 47(2),* 320-341. DOI: 10.1111/bjet.12235

Jordan, K. (2014). Initial trends in enrolment and completion of massive open online courses. *The International Review of Research in Open and Distance Learning, 15(1),* 133-160.

Jordan, K. (2015). Massive open online course completion rates revisited: Assessment, length and attrition. *The International Review of Research in Open and Distance Learning,* 16(3), 341-358.

Ke, F., Xie, K. (2009). Toward deep learning for adult students in online courses. *The Internet and Higher Education, 12(3-4),* 136-145. DOI: 10.1016/j.iheduc.2009.08.001

Khan, A., Baharudin, B., Lee, L. H., Khan, K. (2010). A review of machine learning algorithms for text-documents classification. *Journal of Advances in Information Technology, 1(1),* 4-17.

Kleinbaum, D. G., Klein, M. (2012). *Survival analysis: A self-learning text. Third edition.* New York, NY: Springer.

Krathwohl, D. R. (2002). A revision of Bloom's taxonomy: An overview. *Theory into practice, 41(4),* 212-218

LeFlay, K., Groves, M. (2003). Using online forums for encouraging higher-order thinking and deep learning in an undergraduate Sport Sociology module. *Journal of Hospitality, Leisure, Sport, and Tourism Education, 13,* 226-232.

Lewis, A., & Smith, D. (1993). Defining higher order thinking. *Theory into Practice, 32,* 131-137. https://doi.org/10.1080/00405849309543588

Liyanagunawardena, T.R., Parslow, P. and Williams, S.A. (2014). Dropout: MOOC participants' perspective. *EMOOCs 2014, the Second MOOC European Stakeholders Summit, 10-12 February 2014, Lausanne, Switzerland,* (pp. 95-100).

Marland, P., Patching, W., & Putt, I. (1992). Thinking while studying: A process tracing study of distance learners. *Distance education, 13(2),* 193-217.

Mayer, R. E. (2014). Cognitive theory of multimedia learning. In Mayer, R. E. (eds), *The Cambridge Handbook of Multimedia Learning, second edition* (pp. 43-71). New York, NY: Cambridge University Press.

McLoughlin, D., Mynard J. (2009). An analysis of higher order thinking in online discussions. *Innovations in Education and Teaching International, 46(2),* 147-160. DOI: 10.1080/14703290902843778

Moreno, A., Redondo, T. (2016). Text analytics: The convergence of big data and artificial intelligence. *International Journal of Interactive Multimedia and Artificial Intelligence, 3(6),* 57-64, DOI: 10.9781/ijimai.2016.369

Nelson, S. (2018). *Measuring our first eight courses.* Retrieved from: https://about.futurelearn.com/blog/measuring-our-first-eight-courses

Newmann, F. M. (1990). Higher order thinking in teaching social studies: a rationale for the assessment of classroom thoughtfulness. *Journal of Curriculum Studies, 22(1),* 41-56. DOI: https://doi.org/10.1080/0022027900220103

Offir, B., Lev, Y., & Bezalel, R. (2008). Surface and deep learning processes in distance education: Synchronous versus asynchronous systems. *Computers & Education, 51,* 1172– 1183.

Onah, D. F., Sinclair, J., Boyatt, R. (2014). Dropout rates of massive open online courses: Behavioural patterns. *6th International Conference on Education and New Learning Technologies, Barcelona, Spain, 7-9 Jul 2014.* (pp. 5825-5834).

Rosé, C., Wang, Y.C., Cui, Y., Arguello, J., Stegmann, K., Weinberger, A., Fischer, F. (2008). Analyzing collaborative learning processes automatically: Exploiting the advances of computational linguistics in computer-supported collaborative learning. *Computer-Supported Collaborative Learning, 3,* 237-271. DOI: 10.1007/s11412-007-9034-0

Shah, D. (2018). *A product at every price: A review of MOOC stats and trends in 2017.* Retrieved from: https://www.class-central.com/report/moocs-stats-and-trends-2017/

Skiba, D. J. (2012). Disruption in higher education: Massively open online courses (MOOCs). *Nursing education perspectives, 33(6),* 416-417.

Smalbergher, I. (2017*). Learning analytics towards identifying the processes of higher order thinking in online discussions of MOOCs* (Master thesis). Retrieved from: http://essay.utwente.nl/74246/

Spector J. M. (2017). A critical look at MOOCs. In: Jemni M., Kinshuk, Khribi M. (eds) *Open Education: from OERs to MOOCs. Lecture Notes in Educational Technology,* 135-147. Springer, Berlin, Heidelberg.

Steffens, K. (2015), Competences, learning theories and MOOCs: Recent developments in lifelong learning. *European Journal of Education*, *50*, 41–59. DOI: 10.1111/ejed.12102

Stephens-Martinez, K., Hearst, M.A., & Fox, A. (2014). Monitoring MOOCs: Which information sources do instructors value?. *In Proceedings of the first ACM conference on Learning @ Scale* (pp. 79-88).

Stracke, C. M. (2017). Why we need high drop-out rates in MOOCs: New evaluation and personalization strategies for the quality of open education. In M. Chang, N.-S. Chen, R. Huang, Kinshuk, D. G. Sampson, & R. Vasiu (Eds.), *The 17th IEEE International Conference on Advanced Learning Technologies (ICALT 2017)* (pp. 13-15). IEEE: Computer Society. DOI: 10.1109/ICALT.2017.109

Swinnerton, B., Hotchkiss, S., and Morris, N. P. (2017) Comments in MOOCs: who is doing the talking and does it help?. *Journal of Computer Assisted Learning*, 33: 51–64. DOI: 10.1111/jcal.12165.

Tausczik, Y. R., Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology, 29(1)*, 24-54. DOI: 10.1177/0261927X09351676

Tucker, C., Pursel, B. K., & Divinsky, A. (2014). Mining student-generated textual data in MOOCs and quantifying their effects on student performance and learning outcomes. *Computers in Education Journal, 5(4)*, 84-95.

Vardi, M. Y. (2012). Will MOOCs destroy academia? *Communications of the ACM, 55(11)*, 5. DOI: 10.1145/2366316.2366317

Wang, X., Wen, M., Rosé, C.P. (2016), Towards triggering higher-order thinking behaviors in MOOCs. *The 6th International Conference on Learning Analytics & Knowledge, Edinburgh* (pp. 398-407). DOI: 10.1145/2883851.2883964

Wen, M., Yang, D., Rosé, D. (2014). Linguistic reflections of student engagement in massive open online courses. In *Proceedings of the International Conference on Weblogs and Social Media* (pp. 525-534).

Yousef, A.M.F., Chatti M.A., Schroeder U., Wosnitza M., Jakobs H. (2015). The state of MOOCs from 2008 to 2014: A critical analysis and future visions. In: Zvacek S., Restivo M., Uhomoibhi J., Helfert M. (eds) *Computer Supported Education. Communications in Computer and Information Science, vol 510*, (pp. 305-327). Springer, Cham.

Zhu, E. (2006). Interaction and cognitive engagement: An analysis of four asynchronous online discussions. *Instructional Science, 34*, 451-480. DOI: 10.1007/s11251-006-0004-0

Appendices

Appendix A: Description of the course content

Step	Title	Content type
Week 1: What is eHealth?		
1.1	Introduction to the course	Video
1.2	Set your goals for this course	Discussion
1.3	What do you know about eHealth?	Discussion
1.4	Welcome to Week 1	Video
1.5	Identifying eHealth	Quiz
1.6	What about eHealth?	Article
1.7	Why eHealth?	Article
1.8	Three domains of eHealth	Article
1.9	Experience eHealth yourself	Article
1.10	Share your own examples	Discussion
1.11	Benefits of eHealth	Article
1.12	Barriers to eHealth	Article
1.13	Recognizing benefits and barriers	Quiz
1.14	Do the benefits outweigh the barriers?	Discussion
1.15	The holistic approach: what & why?	Video
1.16	The holistic approach: a roadmap	Article
1.17	The holistic approach: an example	Article
1.18	What did you learn?	Test
1.19	Structure of the course	Article
1.20	Take your knowledge of eHealth further at the UT	Article
1.21	Upcoming conference: supporting health by technology	Article
Week 2: How can we combine technology and healthcare		
2.1	Welcome to week 2	Video
2.2	The rise of eHealth	Article
2.3	Check your knowledge on the three domains	Quiz
2.4	Examples of self-care and prevention	Article
2.5	Self-care and prevention: the case	Video
2.6	How would you address the case?	Discussion
2.7	Self-care and prevention in practice: an example	Article
2.8	Examples of supportive care	Article
2.9	Supportive care in practice: the case	Video
2.10	How would you address the case?	Discussion
2.11	Supportive care in practice: an example	Article
2.12	Examples of societal health	Article
2.13	Societal health in practice: the case	Video
2.14	How would you address the case?	Discussion
2.15	Societal health in practice: an example	Article
2.16	What did you learn	Test
2.17	Looking back this week	Discussion
2.18	Learn how to be happier and help us with research	Article
Week 3: How can we create appealing designs?		
3.1	Welcome to week 3	Video
3.2	What do you already know?	Quiz
3.3	What is bad design?	Article

3.4	How can we design good technology?	Article
3.5	Why use the context when designing eHealth	Article
3.6	What is the value?	Article
3.7	Why are requirements required?	Article
3.8	A case from practice	Article
3.9	Which requirements did you find?	Discussion
3.10	Which requirements did we find?	Article
3.11	What is prototyping?	Article
3.12	Integrating requirements in a prototype	Video
3.13	Practicing with prototyping methods	Discussion
3.14	Show your prototype	Article
3.15	What is usability testing?	Article
3.16	Methods for usability testing	Article
3.17	Usability testing with users: an example	Video
3.18	Usability testing with experts: an assignment	Discussion
3.19	What did you learn?	Test
3.20	The complexity of ehealth development	Discussion
Week 4: How can we change behaviour with technology?		
4.1	Welcome to week 4	Video
4.2	Why do we want to change behaviour?	Article
4.3	Your own experience with behaviour change	Discussion
4.4	Why are behaviour change theories important?	Article
4.5	Techniques to change behaviour	Article
4.6	Recognizing behaviour change techniques	Quiz
4.7	Using reinforcement to change behaviour	Video
4.8	Reinforcement in eHealth	Discussion
4.9	Technology to support behaviour change	Article
4.10	What is persuasive technology?	Article
4.11	How can you be persuaded by technology?	Video
4.12	A model to design persuasive technologies	Article
4.13	Using persuasive elements	Article
4.14	Recognizing persuasive elements	Quiz
4.15	Persuasive design in MOOCs	Discussion
4.16	The ethics of eHealth	Video
4.17	What did you learn?	Test
4.18	Rounding up the week	Discussion
4.19	How persuasive do you think it is?	Article
Week 5: How can we help people and organizations use eHealth?		
5.1	Welcome to Week 5	Video
5.2	The importance of good implementation	Article
5.3	Why can implementation be difficult?	Discussion
5.4	Using theory for implementation	Article
5.5	What influences the diffusion of innovations?	Quiz
5.6	Perceived characteristics of eHealth technologies	Article
5.7	Perceived characteristics: an example	Video
5.8	Involving stakeholders during the process	Discussion
5.9	Identifying stakeholders	Article
5.10	Innovativeness of individuals	Article
5.11	How innovative are these individuals?	Quiz
5.12	Identifying barriers in practice?	Discussion
5.13	What are possible barriers for patients and professionals?	Article
5.14	What are possible barriers for the case on supportive care?	Discussion

5.15	The importance of contextual factors	Article
5.16	The relevance of business modeling	Article
5.17	Business modeling in healthcare	Video
5.18	What did you learn?	Test
5.19	Implementation is relevant from the start	Article
5.20	What's next?	Article
Week 6: Why and how does ehealth work?		
6.1	Welcome to week 6	Video
6.2	Why should eHealth be evaluated?	Discussion
6.3	The what and why of evaluation	Article
6.4	eHealth changes the way evaluation is conducted	Article
6.5	The blackbox of eHealth	Video
6.6	What do you know about formative evaluation?	Quiz
6.7	Methods for formative evaluation	Article
6.8	What do we mean with creating by evaluating?	Discussion
6.9	Summative evaluation: impact and uptake	Article
6.10	The impact of online mental health intervention	Article
6.11	The importance of evaluating the impact of healthcare delivery	Discussion
6.12	Uptake: using log data	Video
6.13	Log data and MOOCs	Discussion
6.14	Create an evaluation plan: the case	Article
6.15	Create an evaluation plan: the assignment	Discussion
6.16	What did you lean?	Test
6.17	Wrapping up the course	Article
6.18	What did you learn from this course?	Quiz
6.19	Wrapping up the course: how did it go?	Discussion

Appendix B:
Survival analysis result – Course overall retention pattern

step	surv	n.risk	n.event	%event	std.err	upper	lower	step
1.01	100.00%	2581	126	4.88%	0.004241593	100%	100%	1.01
1.02	95.12%	2455	53	2.16%	0.005000702	95.95%	94.29%	1.02
1.03	93.06%	2402	57	2.37%	0.005673426	94.05%	92.09%	1.03
1.04	90.86%	2345	48	2.05%	0.006159673	91.98%	89.75%	1.04
1.05	89.00%	2297	154	6.70%	0.007388668	90.21%	87.80%	1.05
1.06	83.03%	2143	114	5.32%	0.008071022	84.49%	81.59%	1.06
1.07	78.61%	2029	105	5.17%	0.00857439	80.21%	77.05%	1.07
1.08	74.54%	1924	83	4.31%	0.00890145	76.24%	72.88%	1.08
1.09	71.33%	1841	39	2.12%	0.009035748	73.10%	69.61%	1.09
1.10	69.82%	1802	61	3.39%	0.009222677	71.61%	68.07%	1.10
1.11	67.45%	1741	43	2.47%	0.009338286	69.29%	65.67%	1.11
1.12	65.79%	1698	31	1.83%	0.009413668	67.64%	63.98%	1.12
1.13	64.59%	1667	38	2.28%	0.009497231	66.46%	62.77%	1.13
1.14	63.12%	1629	33	2.03%	0.009562084	65.00%	61.28%	1.14
1.15	61.84%	1596	61	3.82%	0.00966358	63.74%	59.99%	1.15
1.16	59.47%	1535	25	1.63%	0.009698425	61.40%	57.61%	1.16
1.17	58.50%	1510	29	1.92%	0.009734012	60.44%	56.63%	1.17
1.18	57.38%	1481	24	1.62%	0.009759575	59.32%	55.50%	1.18
1.19	56.45%	1457	171	11.74%	0.009841773	58.40%	54.57%	1.19
1.20	49.83%	1286	1	0.08%	0.009841744	51.79%	47.93%	1.20
1.21	49.79%	1285	18	1.40%	0.009840201	51.75%	47.89%	1.21
2.01	49.09%	1267	23	1.82%	0.009835442	51.06%	47.20%	2.01
2.02	48.20%	1244	15	1.21%	0.009830651	50.17%	46.31%	2.02
2.03	47.62%	1229	36	2.93%	0.009813704	49.58%	45.73%	2.03
2.04	46.22%	1193	28	2.35%	0.009795184	48.19%	44.34%	2.04
2.05	45.14%	1165	13	1.12%	0.009784989	47.10%	43.26%	2.05
2.06	44.63%	1152	23	2.00%	0.009764461	46.59%	42.76%	2.06
2.07	43.74%	1129	29	2.57%	0.009734012	45.70%	41.87%	2.07
2.08	42.62%	1100	12	1.09%	0.009719912	44.57%	40.75%	2.08
2.09	42.15%	1088	11	1.01%	0.009706212	44.10%	40.29%	2.09
2.10	41.73%	1077	5	0.46%	0.009699738	43.67%	39.87%	2.10
2.11	41.53%	1072	10	0.93%	0.009686327	43.48%	39.68%	2.11
2.12	41.15%	1062	10	0.94%	0.009672297	43.09%	39.29%	2.12
2.13	40.76%	1052	6	0.57%	0.00966358	42.70%	38.91%	2.13
2.14	40.53%	1046	7	0.67%	0.009653126	42.47%	38.68%	2.14
2.15	40.26%	1039	3	0.29%	0.009648551	42.19%	38.41%	2.15
2.16	40.14%	1036	10	0.97%	0.009632896	42.08%	38.29%	2.16
2.17	39.75%	1026	12	1.17%	0.009613277	41.69%	37.91%	2.17
2.18	39.29%	1014	92	9.07%	0.009432062	41.22%	37.45%	2.18
3.01	35.72%	922	12	1.30%	0.00940431	37.62%	33.92%	3.01
3.02	35.26%	910	24	2.64%	0.009345869	37.15%	33.46%	3.02
3.03	34.33%	886	16	1.81%	0.009304705	36.21%	32.54%	3.03
3.04	33.71%	870	24	2.76%	0.009239595	35.58%	31.93%	3.04
3.05	32.78%	846	15	1.77%	0.009196817	34.64%	31.02%	3.05
3.06	32.20%	831	12	1.44%	0.009161422	34.05%	30.44%	3.06
3.07	31.73%	819	10	1.22%	0.009131121	33.58%	29.99%	3.07
3.08	31.34%	809	8	0.99%	0.009106348	33.19%	29.60%	3.08
3.09	31.03%	801	5	0.62%	0.009090623	32.87%	29.30%	3.09
3.10	30.84%	796	12	1.51%	0.009052115	32.67%	29.11%	3.10
3.11	30.38%	784	5	0.64%	0.009035748	32.20%	28.65%	3.11

3.12	30.18%	779	8	1.03%	0.009009164	32.01%	28.46%	3.12
3.13	29.87%	771	7	0.91%	0.008985498	31.69%	28.16%	3.13
3.14	29.60%	764	5	0.65%	0.008968361	31.42%	27.89%	3.14
3.15	29.41%	759	12	1.58%	0.008926433	31.22%	27.70%	3.15
3.16	28.94%	747	3	0.40%	0.008915774	30.75%	27.24%	3.16
3.17	28.83%	744	9	1.21%	0.008883365	30.63%	27.13%	3.17
3.18	28.48%	735	6	0.82%	0.008861398	30.27%	26.79%	3.18
3.19	28.24%	729	4	0.55%	0.008846592	30.04%	26.56%	3.19
3.20	28.09%	725	6	0.83%	0.008824138	29.88%	26.41%	3.20
3.21	27.86%	719	34	4.73%	0.008691254	29.64%	26.18%	3.21
4.01	26.54%	685	6	0.88%	0.008666787	28.30%	24.89%	4.01
4.02	26.31%	679	10	1.47%	0.008625316	28.06%	24.66%	4.02
4.03	25.92%	669	17	2.54%	0.008552792	27.67%	24.28%	4.03
4.04	25.26%	652	6	0.92%	0.008526577	26.99%	23.64%	4.04
4.05	25.03%	646	2	0.31%	0.008517767	26.76%	23.41%	4.05
4.06	24.95%	644	2	0.31%	0.008508919	26.68%	23.34%	4.06
4.07	24.87%	642	7	1.09%	0.008477665	26.60%	23.26%	4.07
4.08	24.60%	635	5	0.79%	0.008455064	26.32%	23.00%	4.08
4.09	24.41%	630	2	0.32%	0.008445958	26.12%	22.81%	4.09
4.10	24.33%	628	2	0.32%	0.008436815	26.04%	22.73%	4.10
4.11	24.25%	626	5	0.80%	0.008413793	25.97%	22.66%	4.11
4.12	24.06%	621	7	1.13%	0.008381164	25.77%	22.47%	4.12
4.13	23.79%	614	3	0.49%	0.008367037	25.49%	22.20%	4.13
4.14	23.67%	611	4	0.65%	0.008348067	25.37%	22.09%	4.14
4.15	23.52%	607	3	0.49%	0.008333737	25.21%	21.94%	4.15
4.16	23.40%	604	3	0.50%	0.00831932	25.09%	21.82%	4.16
4.17	23.29%	601	1	0.17%	0.008314495	24.97%	21.71%	4.17
4.18	23.25%	600	5	0.83%	0.008290221	24.93%	21.67%	4.18
4.19	23.05%	595	27	4.54%	0.008154814	24.74%	21.48%	4.19
5.01	22.01%	568	6	1.06%	0.008123708	23.66%	20.47%	5.01
5.02	21.77%	562	10	1.78%	0.008071022	23.43%	20.24%	5.02
5.03	21.39%	552	4	0.72%	0.008049649	23.03%	19.86%	5.03
5.04	21.23%	548	7	1.28%	0.00801183	22.87%	19.71%	5.04
5.05	20.96%	541	7	1.29%	0.007973473	22.59%	19.45%	5.05
5.06	20.69%	534	2	0.37%	0.007962415	22.31%	19.18%	5.06
5.07	20.61%	532	2	0.38%	0.007951311	22.23%	19.11%	5.07
5.08	20.53%	530	2	0.38%	0.007940163	22.15%	19.03%	5.08
5.09	20.46%	528	5	0.95%	0.007912096	22.07%	18.96%	5.09
5.10	20.26%	523	4	0.76%	0.007889437	21.88%	18.77%	5.10
5.11	20.11%	519	5	0.96%	0.007860855	21.72%	18.62%	5.11
5.12	19.91%	514	2	0.39%	0.007849341	21.52%	18.43%	5.12
5.13	19.84%	512	2	0.39%	0.007837781	21.44%	18.36%	5.13
5.14	19.76%	510	1	0.20%	0.007831983	21.36%	18.28%	5.14
5.15	19.72%	509	4	0.79%	0.007808675	21.32%	18.24%	5.15
5.17	19.57%	505	2	0.40%	0.00779695	21.16%	18.09%	5.17
5.18	19.49%	503	2	0.40%	0.007785178	21.08%	18.02%	5.18
5.19	19.41%	501	6	1.20%	0.007749572	21.00%	17.94%	5.19
5.20	19.18%	495	21	4.24%	0.007621482	20.76%	17.72%	5.20
6.01	18.36%	474	4	0.84%	0.007596456	19.92%	16.93%	6.01
6.02	18.21%	470	9	1.91%	0.007539393	19.76%	16.78%	6.02
6.03	17.86%	461	4	0.87%	0.007513691	19.40%	16.44%	6.03
6.04	17.71%	457	3	0.66%	0.007494276	19.24%	16.29%	6.04
6.05	17.59%	454	2	0.44%	0.007481265	19.12%	16.18%	6.05
6.06	17.51%	452	6	1.33%	0.007441909	19.04%	16.11%	6.06
6.07	17.28%	446	4	0.90%	0.007415399	18.80%	15.88%	6.07
6.09	17.13%	442	1	0.23%	0.007408737	18.64%	15.73%	6.09

6.10	17.09%	441	4	0.91%	0.00738195	18.60%	15.69%	6.10
6.11	16.93%	437	2	0.46%	0.007368473	18.44%	15.54%	6.11
6.13	16.85%	435	1	0.23%	0.007361713	18.36%	15.47%	6.13
6.14	16.82%	434	4	0.92%	0.007334532	18.32%	15.43%	6.14
6.15	16.66%	430	1	0.23%	0.007327702	18.16%	15.28%	6.15
6.16	16.62%	429	9	2.10%	0.007265576	18.12%	15.25%	6.16
6.17	16.27%	420	4	0.95%	0.007237584	17.76%	14.91%	6.17
6.18	16.12%	416	21	5.05%	0.00708666	17.60%	14.76%	6.18
6.19	15.30%	395	21	5.32%	0.006928751	16.76%	13.98%	6.19
6.20	14.49%	374	NA	NA	NA	15.91%	13.19%	6.20