

PAPER

Analysis of Students' Behavior Watching iMooX Courses with Interactive Elements

Daniel Dohr, Josef Wachtler,
Martin Ebner()

Educational Technology, Graz
University of Technology,
Graz, Austria

mebner@gmx.at

ABSTRACT

Digital learning technologies are becoming increasingly important for our modern educational system. In addition to teaching methods that incorporate interactivity, these approaches benefit students' overall learning experience and success by enhancing their attention and fostering a positive attitude towards the learning content being presented. Interactivity comes in various forms, and while a combination of distinct activities is beneficial, some are more effective at engaging students. Using digital technologies in an educational environment opens up new possibilities for students, teachers, and researchers. It provides new insights into learning behavior and enables the collection of interaction information. This data could, for example, show how often a video was paused or at what point students lost interest and left, but gaining such knowledge requires further processing. The use of visualizations that depict behavior, such as the change of attention over time, can be an effective way to present extracted information. Therefore, our research focuses on developing an application that enables us to generate various visualizations from the collected data. A single command-line input will be sufficient to create them. Furthermore, a video course was created from which we collected behavioral data. Our results aim to showcase the benefits of interactivity, and that the created figures can be used for data evaluation verifies the versatility of the generated visualizations.

KEYWORDS

e-education, visualization, learning behavior, massive open online courses (MOOCs), teaching

1 INTRODUCTION

The use and importance of digital learning technologies in our modern society's education are steadily increasing because they enable lecturers to combine effective teaching methods with interactive videos. The use of digital environments not only changes the possibilities for teachers to convey their knowledge, but it also improves the means for researchers to gather information and data on students' learning behavior. The data collected through technology-enhanced learning

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provides valuable insights into the learning process, enabling us to enhance learning efficiency, success, and overall experience [1]. Interactivity plays a major role in modern teaching methods, especially when conveying complex material to an audience. As stated in [2], students benefit tremendously from the use of interactive teaching methods, and interactive videos are a powerful tool to facilitate this.

In order to examine the impact of such teaching methods on learning behavior and determine their effectiveness, it is necessary to process the collected data and present it in a form that is easily analyzable. For this task, visual representations are very well suited. They allow us to spot differences immediately and make it possible to compare different videos. Therefore, the development of a tool that generates these diagrams is necessary. Because not all interactions support and benefit students' learning efforts equally, it is necessary to assess the effectiveness of the visualizations. These requirements led us to conduct research on how students' behavior in interactive learning videos can be visualized and analyzed. Therefore, we formulate the following research question: "How can students' behavior in interactive learning videos be visualized and analyzed?"

For this analysis, it is important to first understand the definition of learning behavior and the factors that can influence students' attention in their learning environment.

2 RELATED WORK

The acronym STEM represents the fields of science, technology, engineering, and mathematics, all disciplines that our modern society deems crucial for progress [3]. STEM education can be viewed as an interdisciplinary approach to impart knowledge in the fields of science, technology, engineering, and mathematics, with the goal of achieving economic and technological progress [4]. The need for high levels of technical literacy among the general population of any state establishes a strong link between industry and education [5]. As described in [6], the demand for workers who are proficient in one of the STEM fields has only increased over the last few decades. This highlights the importance of STEM fields for the global economy.

Massive open online courses (MOOCs) enable teachers from around the globe to offer the learning content they have created to a wide online audience without being limited by location or time constraints. Furthermore, by reducing dependence on the instructor, online learning platforms offer great scalability. Additionally, these platforms provide free access to learning materials, which contributes to their popularity [7].

As described in [8], MOOCs make it possible to enhance "student-to-student" interactions, which improves the retention rate. The concept of MOOCs has a significant impact on education, providing knowledge to users at various levels, ranging from beginner to advanced. Also, different learning types are supported by the use of videos, quizzes, and forums. Furthermore, non-technical knowledge, including rhetoric and writing, is promoted, which indirectly benefits STEM [9]. The versatility of MOOCs makes them a good fit for STEM education. For our research, we created a video series that imparts knowledge to students about a significant computer science concept, object-orientation.

To analyze students' learning behavior, researchers must understand how they learn and what keeps them engaged. Furthermore, it is crucial for the analysis to be aware of the students' needs, learning behaviors, and indicators. The term "learning behavior" is described by [10] as the behavior that a person needs to possess in order to effectively learn the presented content in a group setting or classroom. While the

teacher's role is to cultivate such behavior in their students, we can assume that our audience already possesses a certain degree of such behavior, and we can focus on the rating of the indicators. There are various learning behaviors shown by [11], including communication, independent work, and participation, to name a few. The teachers can support such behaviors to enhance the learning efforts and ultimately improve the learning experience. Every behavior also has observable indicators that help to assert them. However, measuring some of them can be quite challenging. An indicator of motivation, for example, is the willingness to independently research information about a task or topic [10]. Depending on the learning environment, the significance of certain behaviors may vary.

One of the most important attributes of learning is the attention span. It is a prerequisite for learning and can be seen as a state of mental alertness or focus that enables one to focus on the presented content. Human attention is selective, and any information considered unnecessary is filtered out [12]. If students can concentrate on the material, it will be easier for them to remember important details and facts later. Naturally, they are unable to maintain their focus over extended periods, and their minds begin to wander [13]. As described in [14], the loss of focus can occur in any learning environment, which can result in a decrease in test scores. Therefore, teaching methods that capture attention and minimize unnecessary distractions are crucial in any classroom.

The concept of interactive teaching comes into play here. The teaching progress involves the interaction between lecturers and their students to transfer knowledge. As outlined by [15], there are three forms of teaching: the passive method, the active method, and the interactive method. The passive style of teaching focuses on the lecturer, with students primarily learning through listening. In contrast, the active learning method emphasizes student participation in the learning process [15].

As described in [16], auditory learners benefit from MOOCs, demonstrating high learning effectiveness and attention scores. Videos, in general, are a powerful tool for conveying learning material [17, 18]. With the rise of technology-enhanced learning, the possibilities of imparting knowledge have increased dramatically. [19] describes videos as one of the most significant forms of digital media. The reason for this might be the increased engagement of students when using active teaching methods. [20] conducted a study and showed that students who used interactive videos learned faster than their counterparts who watched traditional videos. Technologically enhanced learning not only benefits students but also researchers. As described in [21], several techniques help researchers assess students' learning behavior.

3 LIVE

Interaction improves learning for students by directing their attention to essential content. The LIVE platform is a web application that enables lecturers to integrate various types of interactions into their videos. The interactive elements are integrated into the videos, enabling the platform to gather information about students' learning processes. Only registered and authenticated users can access the application. The platform also provides information about student attendance. An algorithm was developed to track student attendance by using recorded timespans of video-watching to calculate an attendance level. The collection of learning data, combined with calculated attendance, allows researchers to use them for assessments and visualizations [22]. The current version of the LIVE platform offers its users four different types of interactions. These types define how and who can trigger the associated interactions.

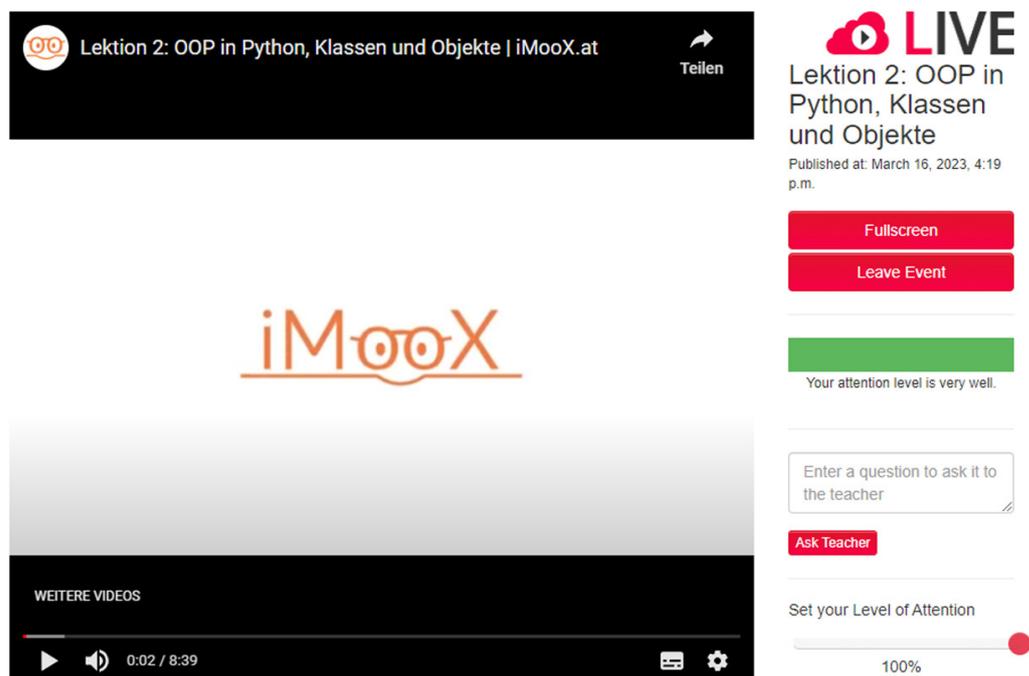


Fig. 1. An iMooX on-demand video with the LIVE user interface

The interactions are categorized by [22] into four types:

1. Automatic interactions: The first type of interaction occurs automatically at random times throughout the videos. The two methods associated with this type are unrelated questions, where students are asked simple questions unrelated to the learning material, and CAPTCHAs.
2. Student-triggered interactions: As the name suggests, students have the ability to initiate this type of interaction. It is accessible through the LIVE user interface depicted in Figure 1. There, students can ask the teacher questions, set their perceived attention level, and report technical issues. The attention level they set is not considered in the platform's calculation of the attention.
3. Teacher-triggered interactions: During an event, teachers can use this type of interaction to ask their students questions in real-time. Currently, there is one available method where teachers can ask students directly. Their responses are taken into consideration when calculating attention.
4. Planned interactions: The last type of interaction occurs at predetermined points in the videos. The three methods are multiple-choice questions, open-text questions, and programming tasks. In contrast to automatic interactions, these interactions require information from the presented learning content.

To effectively visualize the participants' learning behavior, we require a diverse range of information regarding their interactions with the provided learning content. The LIVE platform records student activity and saves it in separate files. Each file contains a unique set of data that is relevant to our research. Because LIVE separates the data into distinct files, we can load only the information we need, saving time during the diagram creation process. Notably, all the available files adhere to a naming convention. Therefore, the file download and subsequent processing are simple. All we need to do is to include the course number in the file name.

4 DATA EVALUATOR

Visualizations allow researchers to effectively analyze students' learning behavior while also enabling them to communicate their findings to an audience. The LIVEData Evaluator was created to generate such diagrams for researchers to utilize. For this purpose, we utilize the data sets from the LIVE platform. This allows us to generate course-specific diagrams that provide valuable insight into the learning behavior of individual courses. Furthermore, it is possible to create composite diagrams. These combinations allow for comparing multiple videos and recorded behavior. These features are designed to provide information about the student's interactions and engagement, aiding in the understanding of the various factors that influence the learning process. LIVEData Evaluator's user interface is a command-line interface (CLI), which enables researchers to interact with the application through a text-based command prompt, where the command and the desired arguments are entered. This method is simple and can be further improved by using scripts to fill in the blanks. The command structure consists of the following arguments:

1. **Mode:** The retrieval of data sets for visualization is a crucial aspect of the application that determines the effectiveness of the tool. The user can choose between two modes, the first being the online mode. If this mode is selected, a POST request will be initiated to the LIVE platform in order to obtain the required files. To access the sets, the user must first log in using their LIVE credentials. There is no need to download the required data if it is already available. The second mode is the offline mode, which is useful when there is no internet connection available or when researchers want to generate a diagram with dummy data, for example. In this mode, the user must provide all .csv files with the correct names and store them in a designated folder.
2. **Diagram type:** If the necessary data is available, the diagram type allows the user to generate the desired graphs. Users can also choose to generate all diagrams at once for added convenience. This is particularly beneficial when used in combination with the online mode, as the required files are promptly downloaded from the platform.
3. **Course list:** The data sets used for further processing are specified in the course list. It is made up of course numbers, separated by commas. The course numbers are determined by the LIVE platform and can be found in the list of records. The list can be accessed through the LIVE platform. The Evaluator is programmed to adjust the size of the diagrams according to the number of lectures. This adaptability enables researchers to compare an unlimited number of courses. This is especially useful when comparing data sets from different lectures or all videos of a single lecture.
4. **Source folder:** This argument specifies the location from which the Evaluator retrieves the downloaded .csv files. When using the online mode, the downloaded .csv files are saved in a predefined location for later processing. If the user chooses the offline mode, the parameter specifies the location to search for the necessary files.
5. **Target folder:** The target folder argument specifies the location where the generated visualizations will be saved. To prevent the creation of folders in unexpected or incorrect folders, the specified path must lead to the correct directory. If this is not the case, the diagram generation will be aborted with an error message.

6. Unique student name: To ensure privacy and avoid bias, the unique student's name is an optional parameter that represents the encrypted name of a student. This parameter is used in the "Watched Parts Single-User Diagram," which displays the parts of a video that were watched multiple times by a specific student. Because they focus on the entire list of participants, all other diagrams currently ignore this parameter.
7. LIVE username: Users must enter their credentials for the LIVE platform when using the online mode to successfully request the required .csv files. To gain access to the researcher tab, where the files are downloaded, researchers must first register on the LIVE platform. The user is prompted to enter the login name and password after entering a valid online command into the command-line interface. After authentication, the data download begins.
8. LIVE password: When using the online version of the command, the user must enter their credentials again. Users are prompted to enter their login information before proceeding with the file download. To protect the entered password, the password input does not display clear text but rather hidden text.

Figure 2 shows an example of how a command for creating diagrams may look. To enhance the usability of the application, help messages have been added to the commands. This provides users with all available options. For this example, the files would be downloaded into the /Source folder. Then all available diagrams would be generated for courses 10, 22, and 81 before saving them into /Target/Plots.

```

Command Structure:
command diagram_type course_list src_location target_location name

Example:
live-dataevaluator\main.py online All 10,22,81 /Source /Target/Plots aug21bd32h

```

Fig. 2. The command structure with example

Depending on the command and, more specifically, on the type of diagram, there are different diagrams available, including the following:

1. Interactions Diagram: The purpose of this diagram is to provide an overview of the student interactions that occur while they engage with the learning content. This includes video stops, resumes, and play actions.
2. Attention Change Diagram: This graph provides an overview of the average attention of students at specific points in the videos. By marking the planned interactions, the researchers can observe their effectiveness.
3. Answer Delay Diagrams: These plots visualize the time it took for students to answer the planned tasks or questionnaires. These delays in answers are represented in the form of box and violin plots.
4. Dropout Ratio Diagram: This plot aims to visualize the dropout ratio of different videos. The number of unique viewers and the total number of views for each second are depicted. This can be used to identify the parts of the lectures where most students drop out.
5. Watched Parts Diagram: These diagrams show which students have watched specific sections of the lectures. It also displays which passages were viewed multiple times to detect comprehension issues.

5 EVALUATION

The MOOC we provide consists of four lectures, and for each lecture, students can complete a self-assessment survey. Furthermore, to complete the section, students are required to take a final quiz, where they could reach up to 10 points. Table 1 shows the results of these quizzes. Notably, participants were only able to fill out the assessment once, while the quiz allowed for multiple attempts. Over the duration of the MOOC, it is evident that students, on average, demonstrated an improvement of 1.54 points between the assessments and the final quizzes. The table also shows that the number of participants decreased from 52 for the first lecture to 30 for the last. The results may indicate whether and to what extent the students have improved, but they do not provide any information about how much of the video the students watched or when they chose to stop. For this, we require additional data sets from the LIVE platform.

Table 1. iMooX assessment and quiz results

	Misc.		Quiz Points	
	Students	#Tries	AVG (All Tries)	AVG. (Best Try)
Assessment Q1	52	-	6.36	6.36
Exam Q1	52	102	7.19	8.69
Improvement	-	-	0.83	2.33
Assessment Q2	25	-	6.53	6.53
Exam Q2	38	58	7.98	9.26
Improvement	-	-	1.45	2.73
Assessment Q3	19	-	6.23	6.23
Exam Q3	33	66	7.23	8.58
Improvement	-	-	1.0	2.35
Assessment Q4	13	-	4.92	4.92
Exam Q4	30	44	7.80	8.81
Improvement	-	-	2.88	3.89
AVG Course	-	-	7.55	8.84
AVG Improvement	-	-	1.54	2.82

As noted previously, we used the data collected from LIVE to create the visualizations. Before we look at those diagrams, we need to address a minor discrepancy between the collected MOOC and LIVE data. As observed in Table 2, the number of students who watched the videos does not match the number of completed quizzes. The reason for this is the fact that students are not required to watch the video in order to take the quiz. The data presented in Table 2 provides information on the number of interactions students will have while watching the video, as well as the percentage of how much of the video was watched by the average student. The remaining information provided by the LIVE platform needs to be processed further in order to be useful.

Table 2. LIVE statistics of the OOP course

	Students	#Interactions	Watch AVG (%)	Duration(s)
Lecture 1	48	2	57.79%	602
Lecture 2	16	2	70.93%	518
Lecture 3	14	2	80.28%	585
Lecture 4	7	2	85.14%	431

Therefore, to gain a better understanding of student learning behavior, the collected data is processed and utilized to generate the visualizations described in the following sections.

5.1 Dropout ratio diagram

Figure 3 depicts the video dropout ratio for each second of the programming course. The y-axis shows the number of total views and the watcher count, which represents the number of individual users who watched the respective section, and hence, each lecture is represented by two lines. For the first lecture, we initially observed strong engagement from 43 unique viewers, and for the first percentages, a total of 72 views. However, the diagram shows a significant decline within views in the 1–15% range. Furthermore, the number of viewers declined to 32. From the 15% mark onwards, both the user and view count gradually decrease until the end of the video.

As for Lecture 2, the diagram shows a major drop in viewership compared to Lecture 1, where 16 students began watching the video. This drop shows the disparity between the data gathered from iMooX, as shown in Table 1, and the viewer statistics from LIVE, as shown in Table 2. While only 16 users watched the video, 38 students took the quiz. A closer examination of the remaining portion of the curve reveals that students probably skipped certain sections of the video, as evidenced by the irregular user curve.

For lecture 3, the user count only decreased slightly, with 14 participants. The watch behavior is similar to that of the previous video. Given that the user count did not decrease further, we assume that the remaining students were highly engaged in the learning content. This assumption will be supported by the attention diagram depicted in Figure 4.

The downward trend continues for Lecture 4. The number of viewers peaked at 7 but remained stable throughout the video. The numbers depicted in this diagram indicate an urgent need for improvement and optimization.

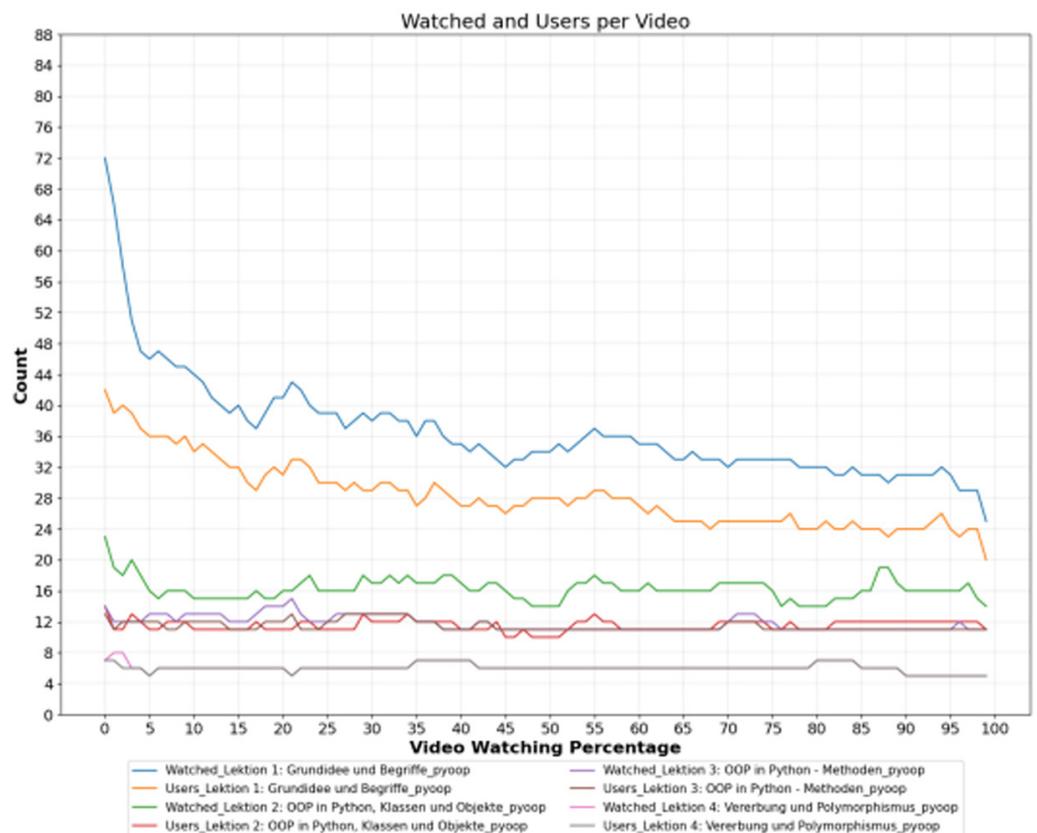


Fig. 3. Drop ratio diagram of the OOP course

5.2 Answer delay diagrams

Figure 4 depicts the amount of time participants needed to answer the LIVE pop-up questions. Each column represents a lesson from the current course. The number of delays for the multiple-choice questions is indicated by the green components. Blue and red parts represent programming tasks and text questions that are not used in these videos. We can observe that the fastest 25% of students had an answer delay of 16 seconds for Lecture 1, whereas the average delay time was around 23 seconds. Furthermore, 75% of the students completed the quiz in less than 29 seconds. The plot's relatively long whiskers indicate an even distribution above the upper limit, as observed in a different version of the answer delay diagram (see Figure 5). There is also an outlier who took up to 58 seconds to respond to the question.

Lecture 2 includes two multiple-choice questions. We can see that the questions in this lecture were answered more quickly than the questions in the previous video. The fastest 25% completed the interaction in 9 seconds, while the average student took around 11 seconds. Furthermore, 75% of the students answered the questions in less than 15 seconds. Our plot shows outliers taking up to 56 seconds to complete the interaction. The boxplot and its whiskers are particularly short, indicating a dense distribution.

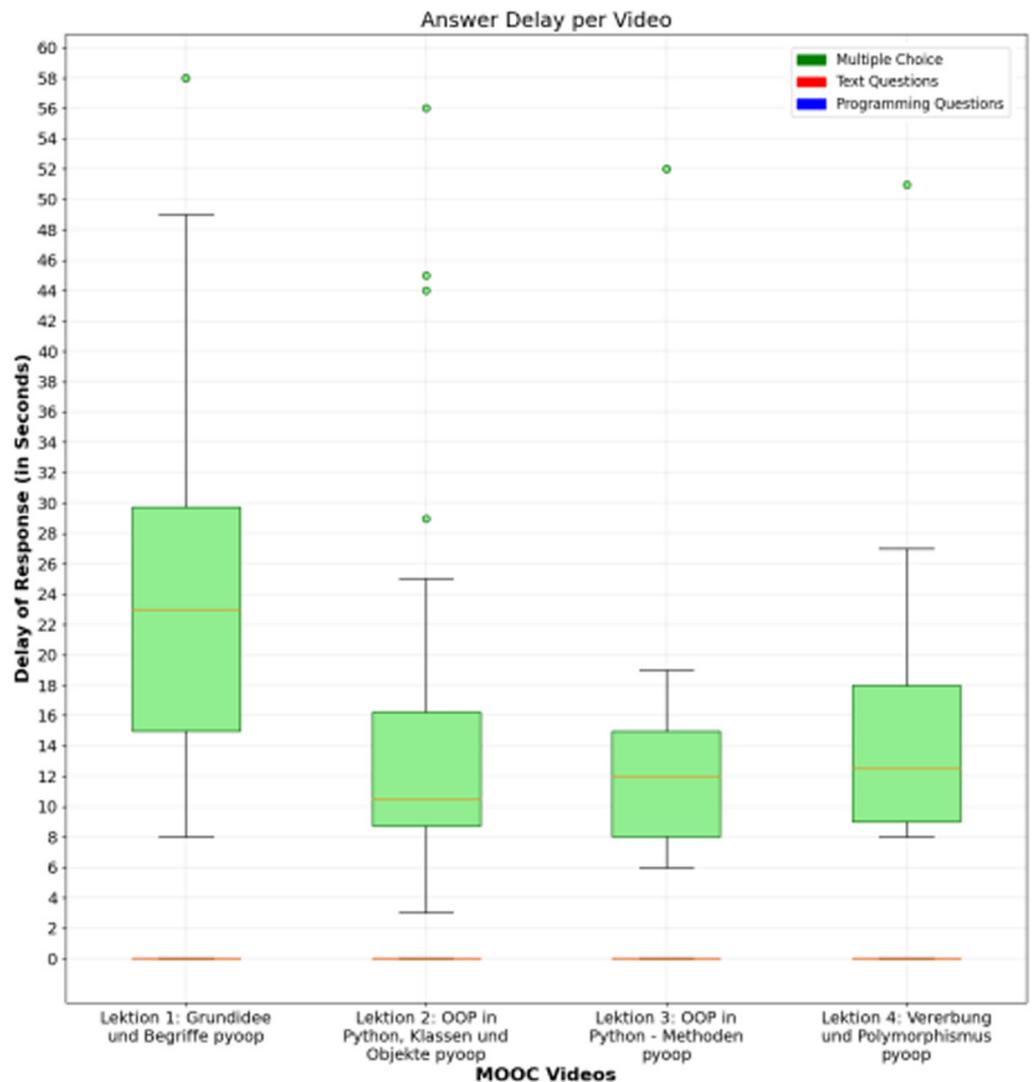


Fig. 4. Drop ratio diagram of the OOP course

The actual distribution is illustrated in Figure 5 using a violin plot. The violin used for this lecture has a thick base.

The answer delays are once again relatively dense in Lecture 3. The question was answered in 8 seconds by the fastest 25% of participants. The average student took approximately 11 seconds to complete the interaction. With only 14 seconds to respond, the upper limit was calculated. The box plot's short whiskers indicate a high concentration of values around the 10-second mark, which is corroborated by the corresponding violin plot. A notable outlier has a time of 51 seconds.

A small box can also be found in the Lecture 4. 25% of the students answered the questions in 9 seconds or less, while the average student answered in 11 seconds. In comparison to previous lectures, the upper limit is 17 seconds. This component, as indicated by the violin plot, extends beyond the previous one, suggesting that the students took more time to answer the questions related to inheritance. The corresponding violin plot confirms a high concentration of values around the 10-second mark. A notable outlier has a time of 51 seconds.

The answer delay diagram distributions and overall fast answer times for all lectures indicate that students understood the presented content and were engaged, leading to these positive results. Lecture 1 appears to have been the most difficult, followed by the final lecture about inheritance.

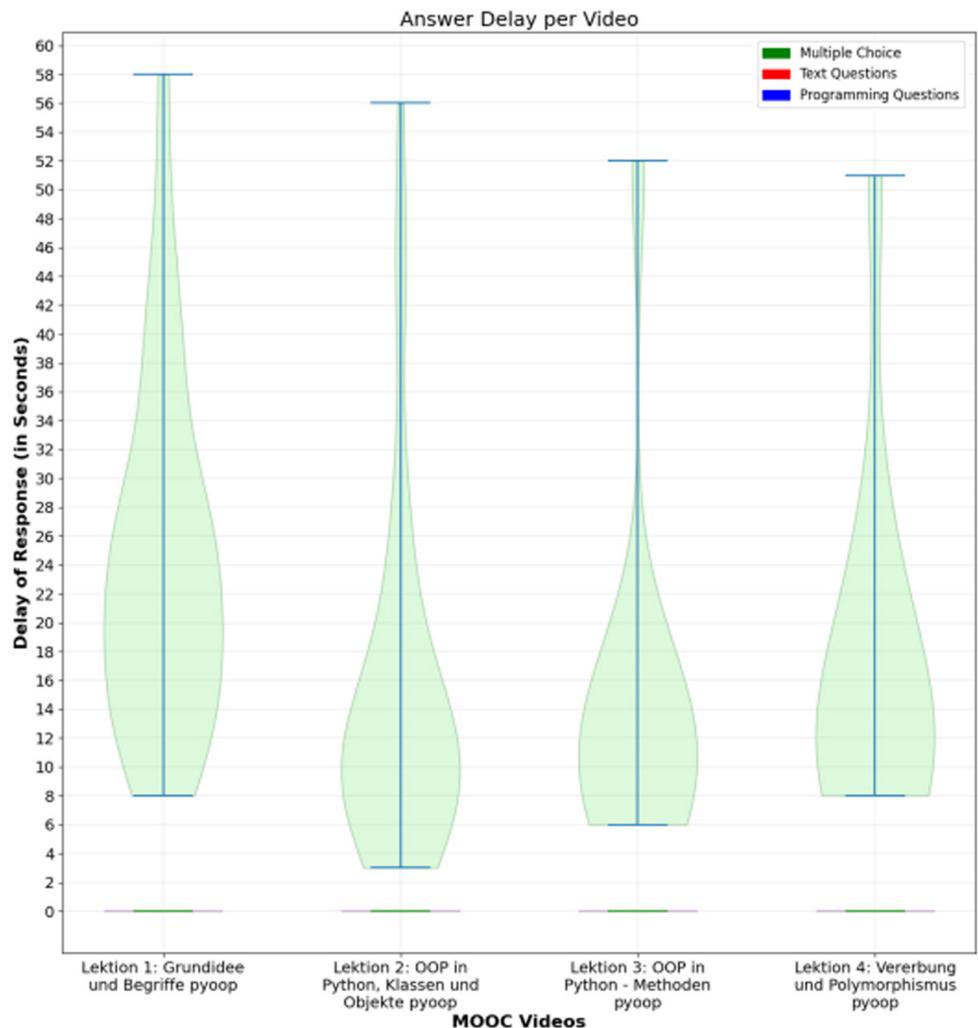


Fig. 5. Violin plot of the answer delays

5.3 Interaction diagram

Not only do the pop-up interactions provide information about the students' learning behavior, but they also offer valuable insights. Figure 6 depicts the students' interaction with the video, including stops, plays, and resumes, indicating the frequency at which the videos were fully viewed. As depicted in Figure 6, there is a noticeable decline in the overall interactions with each video, which aligns with the previously mentioned observations of declining viewership. The first video depicts 220 pauses and 161 resumes. The plot shows 81 starts, but only 21 people completed the entire video. The number of completions matches the one shown in the dropout ratio diagram. In Lecture 2, we observed a significant decrease in viewer interactions, with 98 stops, 25 plays starting from the second zero, and 78 resumes. The participants watched the video ten times in its entirety. Given the numbers in Table 2, this result was to be expected. In Lecture 3, we observe a significant decrease in interactivity compared to the decrease in viewers. Only two viewers left, according to the LIVE data table and the dropout ratio diagram, while interactivity experienced a significant decline. The trend of decreasing interactions continues in the final Lecture 4, with only 39 interactions in total. These figures show a significant decrease in student engagement in the last two videos, highlighting the critical need for improvement.

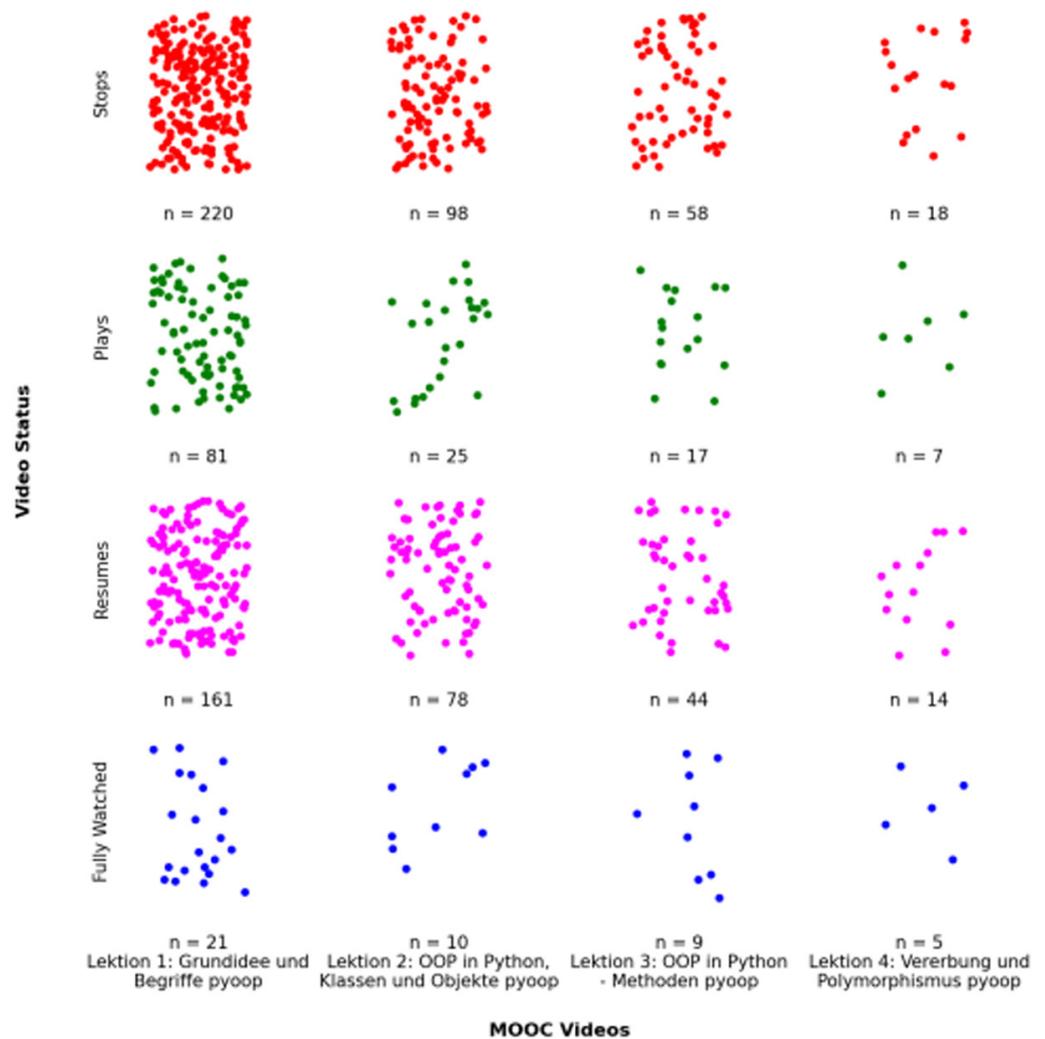


Fig. 6. The number of interactions per video

5.4 Attention change diagram

This type of diagram is used to show researchers how attention levels behaved during the lectures. The LIVE platform calculates the attention levels of individual students based on their interactions with pop-ups and the rest of the user interface. As a result, activities such as pauses and resumes have an impact on values.

According to Figure 7, the average attention level of the students starts at 99% for the first lecture and gradually decreases to 95% within the first three minutes. The diagram illustrates the first automatic pop-up question of the LIVE platform as a vertical red line. The attention value recovers after the interaction, remaining between 96.8% and 95.6% until the next activity at the end of the video, as shown in the figure. The previous diagrams depicted data exclusively obtained from object-oriented programming (OOP) in the Python course. For the attention change, we also want to compare the video of Lecture 1 (OOP) and Lecture 2 of the Basics course.

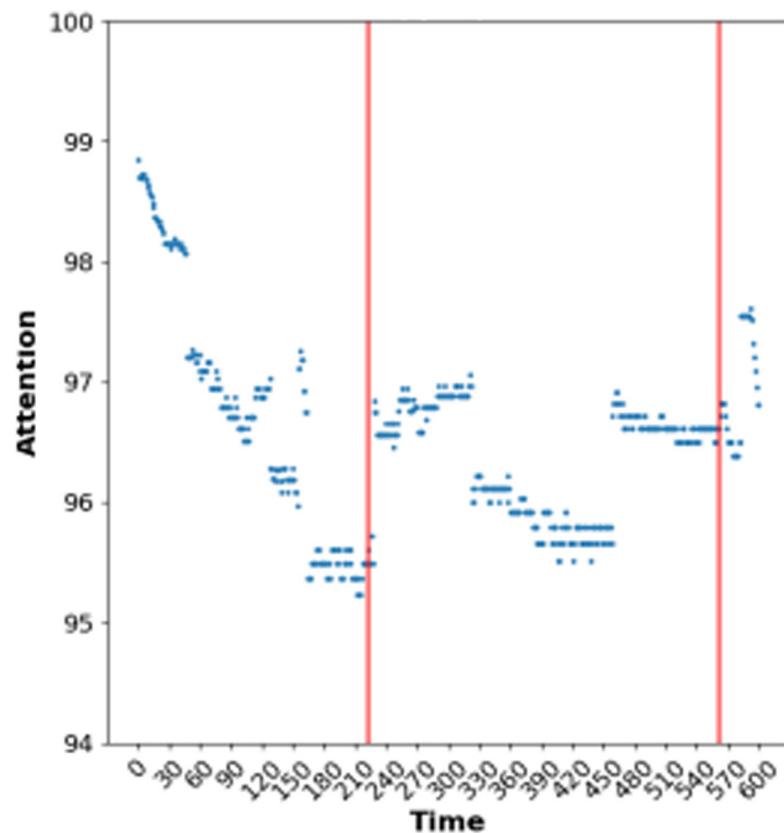


Fig. 7. The change of attention in lecture 1 (OOP)

Figure 8 for the second lecture of the Python Basics course shows a similar pattern. However, the students' attention rapidly declined in the first third of the video, dropping from 95% to 90%. After the interaction, the attention value initially recovered to 92%, but shortly after, it fell to 87% until the next activity of the video. Notably, this activity involved a programming task, which is significantly more interactive than a multiple-choice question. After completing this task, the attention value steadily increased and even surpassed the initial attention level in the video, reaching 95.5%.

While both diagrams depict an increase in attention after the interactions, it is clear that the curve of Lecture 1 is way more jagged than the one shown in Figure 8.

The second curve is more continuous because there are more participants, resulting in a more expressive curve.

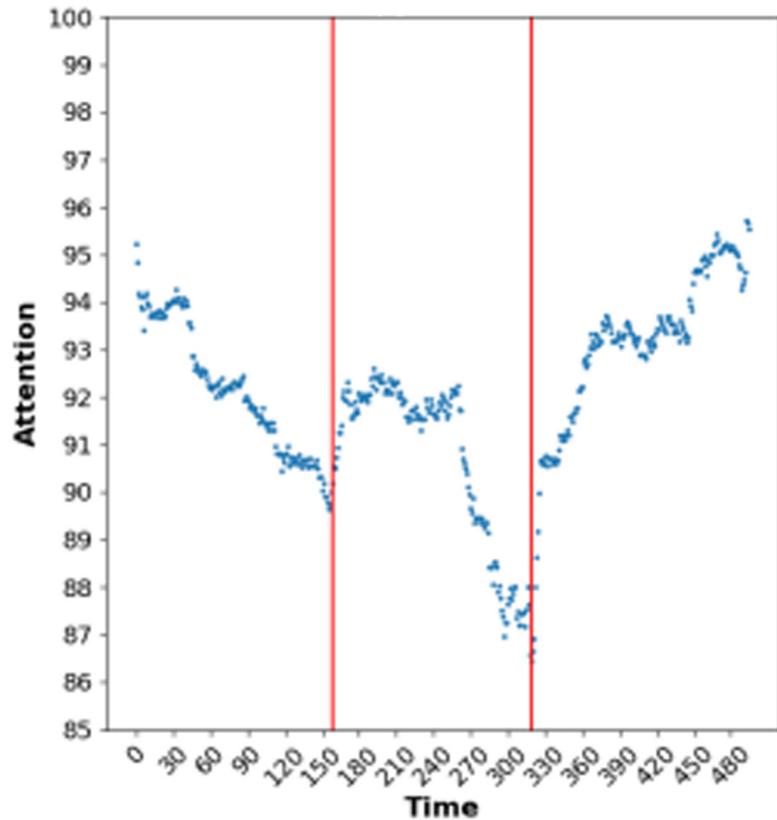


Fig. 8. The change of attention in lecture 2 (Basic)

6 CONCLUSION

Interactivity has a positive impact on students' learning experiences and overall success. Technology-enhanced learning allows for additional data collection on how students interact with the presented content. The effectiveness of interactivity is influenced by various factors, such as the timing of pop-ups and the nature of the task, whether it is a programming task or a multiple-choice question. To examine these influences, we implemented and utilized the LIVEData evaluator to generate diagrams that illustrate the processed data in a manner that researchers can comprehend.

The objective of our research was to address the question of how to visualize and analyze students' learning behavior in interactive learning videos. The tool currently provides researchers with access to seven different diagrams. These visualizations can be created with a single command-line interface (CLI) command. They process the data collected by the LIVE platform. We also provided instructions on how to interpret the diagrams before demonstrating their use in various courses.

We began by analyzing the students' behavior using data provided by the iMooX platform, where the Python courses are hosted. We analyzed the participants' learning efficiency using data from surveys, assessments, and quizzes. A glance at the

point distributions revealed that the number of students was decreasing with each lecture. Using only the MOOC data, however, did not provide a clear understanding of the cause. At this point, the visualizations have provided useful insight into the students' attention, indicating the root cause of the declining retention rate. The diagram analysis provided us with valuable insights into students' attention and course retention rates. Notably, despite the high attention levels, we lost students with each lecture.

The majority of dropouts were recorded during the first lectures. Given the positive attention values and quick response times for the remaining videos, we hypothesize that the dropouts were either overwhelmed by their prior knowledge base or disinterested in the content. The diagrams also revealed another pattern for a different course, which had an excellent retention rate.

In conclusion, the visualization analysis has proven to be a valuable addition to examining students' learning behavior. The use of these illustrations simplifies the comparison of outcomes between different videos and courses. We have answered the research question through our comprehensive explanation of the implementation and detailed analysis of the evaluation results.

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8 AUTHORS

Daniel Dohr is studying software engineering and management at the Graz University of Technology (E-mail: dohr.daniel@gmx.at).

Josef Wachtler is currently working at the Department of Educational Technology at Graz University of Technology as an Edtech-developer. He holds a PhD in computer science and assists in supervising Master's and Bachelor's theses. His research-interests are in the field of video-based learning used in different settings like schools, universities or MOOCs (E-mail: josef.wachtler@tugraz.at).

Martin Ebner is currently Head of the Department Educational Technology at Graz University of Technology and therefore responsible for all university-wide e-learning activities as well as a senior researcher for educational technology (E-mail: mebner@gmx.at).