

# X Modal X Cultural X Lingual X Domain X Site Global OER Network

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## ABSTRACT

X5GON combining various elements such as content understanding, user modelling and personalisation, aims to create a unified and international network of Open Educational Resources. Building on X5Gon, two tools X5Learn and X5Moodle were developed to enhance adoption, ease-of-use, and engagement with OERs, as well as to support teachers and students. We carried a user study to show the impact of each tool. The first study is centred on the Content FlowBar (CFB) a novel interaction technique developed in X5Learn to facilitate the discoverability of video content. The CFB provides semantic “snippets” related to the video content as users browse through a video. A user study was conducted to evaluate the performance and impact of the feature. Overall, we showed how CFB benefited users, as it enhances information seeking and facilitates exploratory behaviour. Moodle is the most important Learning Management System in the world today. Thus, a new tool X5Moodle was developed so OCR educational and scientific resources from X5Gon could be accessed directly from Moodle without any risk for students and teachers. More so, the tool provides complementary ways of finding information, with features such X5-Recommend. X5Moodle was assessed within a course on Machine Learning and Natural Language Processing, at Université de Nantes. During the course, the Jupyter notebooks were used to capture basic analytics from the tool’s usage. From the collected data, an interest map was produced so the teacher could visualise what material students looked at. More so, teachers can get feedback on features used, and on students’ behaviour, so they could respond to potential issues or gap in the student’s knowledge in a timely manner. Indeed, looking at new visualisations from the analytics, teachers can become more aware of the class dynamics and more engaged with the student’s needs. Finally, X5Moodle’s functions provide an alternative, more peer-based way of using a recommender approach to aid students searching for course material.

### 1. CONTENT FLOW BAR STUDY

Videos have become an integral part of education, being used both in the classroom and online. They provide accessible and engaging ways of conveying material and information. There are millions of different kinds available freely online from educational to entertainment. Those intended to be for the educational domain are collectively called Open Educational Resources (OER). Previous research on OER has shown that students responded positively and judged teachers more sensitive to their needs when using OERs (Vojtech and Grissett, 2017). More generally, OERs can foster “access to education for all” and are open in the sense that they can drastically reduce students and educational institutions costs.

A key question, however, is how do learners and teachers, alike, decide which of these from the potentially millions available to watch and how best to learn from them? Moreover, how do they know they are any good – in the sense of the underlying pedagogy, quality and level of engagement they have. Finding content in educational videos can also be time-consuming. Another problem is that users often face a bottleneck: they can only access the content serially and sequentially meaning they cannot predict which part of the content of an OER might be relevant to their needs.

In this WP, we present our new platform X5Learn, which enables teachers access to the vast array of OER - mostly in the form of videos from a number of specialised sources. Our platform has been designed to address this problem of discoverability (Luo et al., 2020; Cortinovis et al. 2019) through the development of a novel interaction technique called the content flowbar.

Previous research has investigated interaction techniques for navigating videos beyond simple timeline interfaces. In relation to how to navigate through videos, Chang et al. (2020) used a voice interface, that enabled navigation through speaking aloud key commands (e.g. jump, go backward), outlining the challenges and benefits of using voice in this context. Kim, et al. (2014) proposed new interaction techniques for educational videos, based on analysing interaction data (using transcript analysis and learner’s interaction history), such as trace, most watched segments in a video, and key search in video-based. Zhao (2015) investigated the efficacy of using a visual navigation system in the context of biomedical OER videos. Features included a visual search tool embedded in the timeline of a video and attaching keywords with each video.

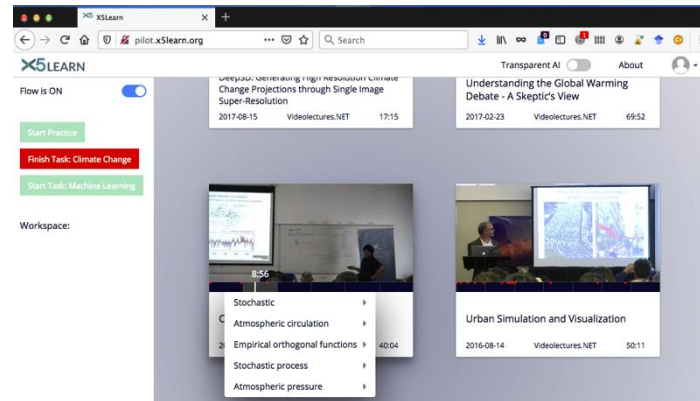
Similarly, we proposed developing a more visual search tool with the aim of facilitating video browsing. Our novel interaction technique, the Content Flow Bar was designed to provide semantic “snippets” of the video content. These can be seen as pop-ups and overlap in a time series bar, allowing the user to see in advance what topics are covered in a video. In doing so, it is intended to provide a better form of navigability. A user study was conducted to evaluate the efficacy of the novel content flow bar in terms of how it helped discoverability and information retrieval. In this report, we first introduce X5Learn in relation to our study, and then describe the study including goals, methodology and findings.

#### 1.2 X5LEARN INTERFACE FOR THE USER STUDY

In XGon 9.3 report, we have given a general overview of the X5Learn interface. Here we describe the interface elements that relate more specifically to the user study. The study was run using the X5Learn platform that was only accessible to



participants and researchers. The study design was constrained to enable the participants to perform a few tasks; (i) to switch the content flowbar on and off, (ii) options to start and end the search, and (iii) study tasks. Figure 1 shows the content flow bar in use for when a user has typed in machine learning in the search box. It shows thumbnails of the selected videos and the relevant topics to machine learning appearing along the timeline.



**Figure 1:** X5 Learn study interface, main window

The Content FlowBar (CFB) provides semantic “snippets” related to a video content that pop up on the screen for different video segments. As part of the CFB, keywords’ definitions are provided in the form of pop-ups which are extracted from Wikipedia (see Figure 2a). This type of cueing is intended to enable the user to see at a glance what a video lecture covers and to be able to stop at particular points to discover more. From the main window, when a participant wants to look further at a segment of a video, they can jump directly to that segment (see Figure 2b). The videoplayer window opens and the video starts at this particular segment. All participants can also explore the videos by moving in their cursor along the video timeline.

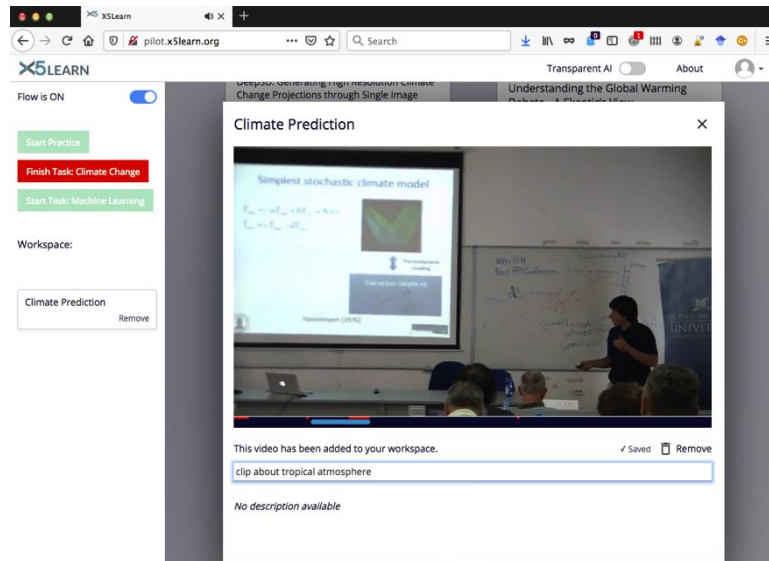


**Figure 2a:** CFB and a definition for stochastic in the main window

**Figure 2b:** pop up window showing ‘play from here’

Once a participant has decided to select a video clip, the selected portion is highlighted in blue on the CFB, and the video title is displayed in the participant’s workspace (see Figure 3).





**Figure 3:** Selecting a video clip to play

## 1.3 CFB USER STUDY

An initial pilot study showed that the CFB was relatively straight forward to use. The study tasks were slightly modified to look at different aspects of information seeking. We added a questionnaire to capture more information on different aspects of the CFB and the ability to extract user interaction logs.

### 1.3.1 Goal of study, research questions

The main user study was designed to compare user performance of our videoplayer with content flowbar tool to a baseline video player. This is a common approach when evaluating videoplayer interactions and interface designs (Jung et al., 2018; Yadav et. al 2018). The goal of the study is to understand and evaluate, how the CFB supports information seeking, facilitate content navigation and support browsing through video content. We also collected some feedback on users' perceptions of the new tool. The main research questions for the tool are as follows:

R1: How does the navigation and browsing compare across the two interfaces: Baseline and content flowbar? What are the differences in terms of information seeking and exploratory behaviour?

R2: What are the values and benefits of using the CFB in terms of time, satisfaction, relevance, success, etc.?

These were broken down into specific hypotheses:

- The content FlowBar provides a better understanding of the video content
- With an ill-defined task, participants will take more time in the CFB condition, as they are more engaged in the video clip selection.
- It is easier/faster to locate and select a video segment for which keywords appeared in the CFB.
- The relevance of the selected video clips should be greater with the CBF.
- The distribution of video clips selected should be more diversified within the CFB condition.
- The CFB should increase user satisfaction, and make finding video clips less frustrating



### 1.3.2 Methodology and study's instruments

The information seeking task that was designed was to find relevant video clips that would be used in teaching. The study is based on a repeated measures design, so each participant does both the control and treatment conditions, using the baseline and enhanced videoplayers. We used counterbalancing to address training effect and fatigue where the participants have to perform a task with and without the CFB. For tasks, we developed two scenarios relating to two subjects: Machine Learning and Climate Change. We provided 18 videos for each subject.

Before the study, all the participants were sent an information sheet and consent form so it could be signed before the session. The study session took place remotely through Zoom. As before, the researcher first gave participants a brief overview of the study, then demoed the X5Learn platform, highlighting the features needed for the study.

The participants first practised using the tool for the topic of “brain” as video content until they felt confident that they could move onto the main study. Then, each participant performed the information seeking task for one of the two topics following the relevant scenario for both conditions: Once both tasks were finished participants were asked to fill in a questionnaire.

**Scenario Climate Change:** “As you are interested in climate change, a friend has asked you to find interesting 2 video clips that illustrate the applications of data science in climate change. Then, can you find 2 video clips that illustrate controversial issues in climate changes. These video clips will serve to initiate a debate in class. As watching videos should not take too long, you will have to select 4 short segments for students to watch (e.g. 5-6 minutes). All 4 clips should be chosen in four different videos.”

**Scenario Machine Learning:** “Some students want to learn about machine learning in your next workshop. As its importance is growing, you are tasked with finding 2 video clips that illustrate key concepts that students can watch at home, and make notes about. Then in the workshop, you will be shown 2 video clips on the applications of machine learning, and discuss it with them. As watching videos should not take too long, you will have to select 4 short segments for students to watch (e.g. 5-6 minutes). All 4 clips should be chosen in four different videos.”

**Videos:** All the videos selected for the study are found on the X5Learn platform. We selected 18 educational videos from each subject. All the videos are from academic conference presentations (or specialised seminars and summer schools). In most cases, the speakers’ PowerPoint have been captured and included in the videos.

**Questionnaire:** We developed a short questionnaire that asked questions about specific aspects of CFB, and especially keywords. We were interested in understanding what roles and functions were associated with the keywords, as well as, the user experiences of using the CFB. The questionnaire contained both open-ended questions and rating states. The questionnaire also contained questions about demography, and teaching experience. Participants were then asked to self-report their knowledge of each of topic.

Participants were asked to rate keywords properties, on a 6-item Likert-scales, from strongly disagree to strongly agree. The keyword properties were derived from user feedback, half had a positive and negative valence. We also asked participants if they wanted to add word (s) to qualify the keywords. Participants were asked to rate statements on the main roles of CBF and to conclude to rate a few statements on the user experience.

### 1.3.3 Interaction Log

We also captured users' interactions using data logs. To integrate and process the raw data from the study log, we specified measures and metrics we wanted to investigate.

#### 1.3.3.1 Performance of CBF

In this kind of study, time is often a major factor used to assess the performance of the novel tool or interaction technique, e.g. would participants be able to perform tasks faster with the new tool? We thus computed the time taken by participants to complete each part of the session (CBF /without CBF) was computed.

#### 1.3.3.2 Exploratory behaviour CFB, comparing with/without CFB

When looking at search results, it can be hard for a user to get started and to decide which video they should look at, thus users rely on cues such as video thumbnails, titles and the video descriptions. As we have seen in the playlist study (see report XGon 9.3), participants mentioned using the video style, to assess suitability of the video for a task. When using the CFB, participants can explore the video content through using the keywords.

Preliminary viewing and searching behaviour (before opening videoplayer):

- Time spent browsing through result list, looking at thumbnails and exploring content cues (video scrapping or /and looking at keywords)

Keywords (browsing patterns): how participants use keywords to explore video content initially:

- Systematic (browse through all the keywords in a video)
- Partial (more than one in a video, more than one segment in a video)
- Almost none, only one at beginning

Videos:

- Time spent in navigating and looking at videos cue before playing one (videoplayers)

#### 1.3.3.3 Information Seeking behaviour with CBF, comparing with/without CFB.

We wanted to understand participants' behaviour and the impact of CBF on tasks, during the different phases of information seeking, or in relation to aspects of the tasks for each condition. These included looking at the diversity and depth of participant selections in terms of:

- Depth: total number of videos visited in each condition, and subject
- Diversity: total numbers of video clips watched, position of clips in sequence, in each condition
- Number of clips watched before each selection, and each condition
- Play Duration: overall in each condition, by task order, and subject
- Comparing video selection (and clips) in each condition

Analysis of keywords, CBF only:

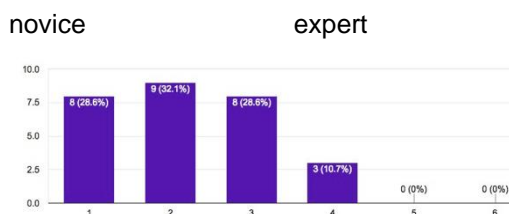
- Browsing behaviour during tasks, and for each subject
- Relation keywords to selected clips (direct, indirect, none)
- Heat map of videos keywords (selected video, clips)
- Frequency of keywords in selected video clips

### 1.3.3.4 Quality control, with or without CBF

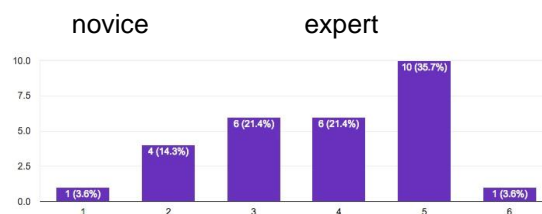
We also wanted to assess the fit between participant's clip selections and the topic under question. We wanted to determine the extent to which video clips selected by participants did fit the overarching topic (e.g. machine learning, or climate change) and subset of that then to be able to distinguish between the quality of different selected clips such as how clips would be rated in terms of clarity or engagement. We did this (i) automatically by comparing the semantic relations of video clip selections with and without CBF and matching keywords to the selected clips and (ii) by having the clips rated for the fitness in terms of the parameters identified for this purpose.

## 1.4 RESULTS FOR THE STUDY

Nearly half of the participants were aged between 30-39 years. We had slightly more male participants (53.6%) than female (46.4%). Their knowledge of the two topics - Machine Learning and Climate Change - were quite different (see Figures 4a and 4b). As can be seen more of the participants rated themselves as expert in machine learning than in climate change.



**Figure 4a:** Climate Change



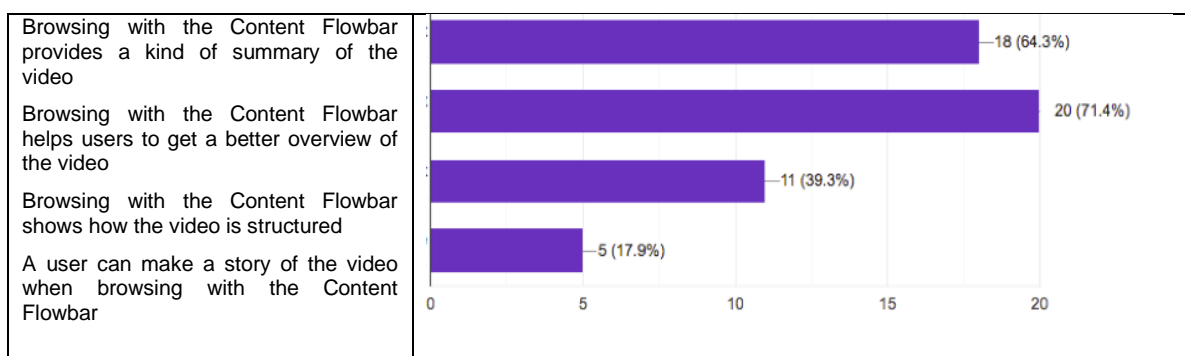
**Figure 4b:** Machine Learning

### 1.4.1 Analysis of rating scales

Results presented in this section are from the rating scales used in the questionnaire.

#### 1.4.1.1. Perceptions of efficacy of the content flowbar

Figure 5 shows the percentages of participants who selected the statements they felt matched how they viewed the content flowbar. They were quite varied but with most agreeing with the statement that it provided an overview of summary of the videos.

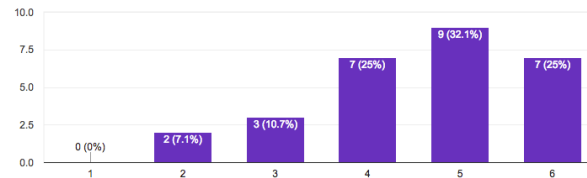


**Figure 5:** CFB, statements describing the potential of the Content Flowbar

As seen in Figure 6, most participants also agreed that the CFB assisted them in selecting video clips. From the participants' answers to the open-ended questions, it was found that the content flowbar was perceived to be a time-saving mechanism: "less time overall than actually preparing a lecture, especially for 18 videos and 4 clips"

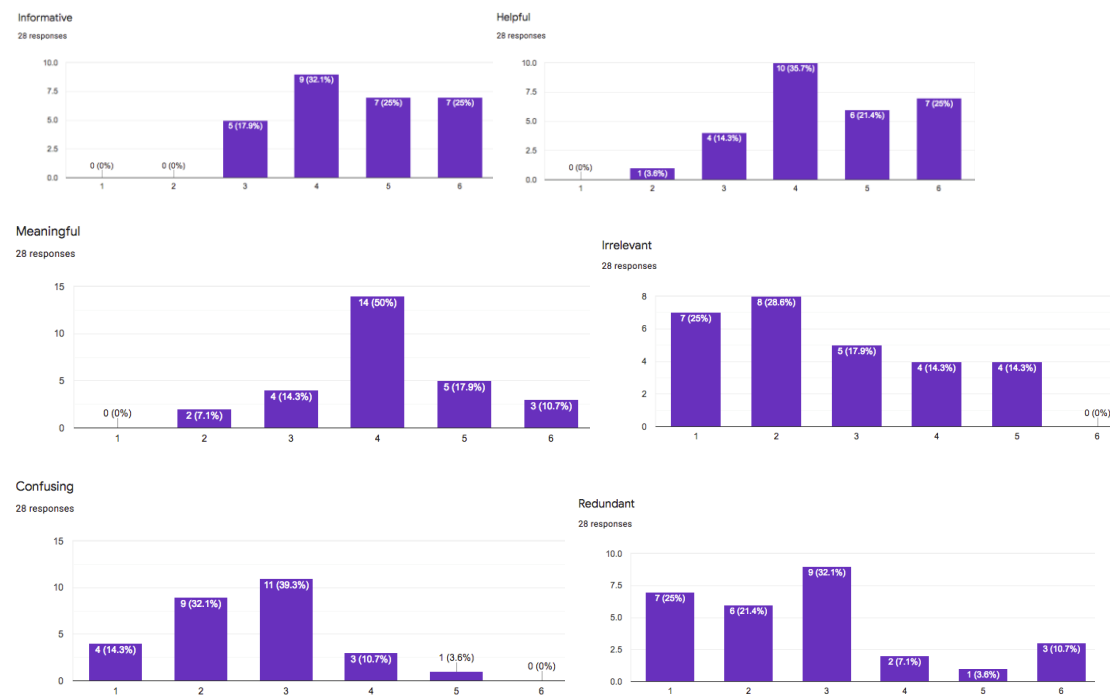
It also helped them to navigate to and choose the right video segment effectively; helped them identify the detail of the topic being spoken about in an easier way than without the content flowbar and helped them to better assess or predict the conversation flow. It also helped them to eliminate irrelevant information: “*even easier to eliminate sources that are irrelevant to what you are looking for*”

The enhanced videoplayer (with the Content Flowbar) made finding video clips easier  
28 responses



**Figure 6:** Percentage responses to the statement about how the CFB helped making finding video clips easier, from strongly disagree to strongly agree.

Participants responses when asked to select keywords according to the following question “selecting a video clip to fulfil the tasks, the keywords were” (see Figure 7) were mainly positive. The proportion of negative ratings varied from 4% (confusing) to 8% (irrelevant). It seems that some keyword characteristics were too similar to the topic heading so participants could not distinguish between them. These were usually keywords generated by the wikifier for a video were not related to the video content.

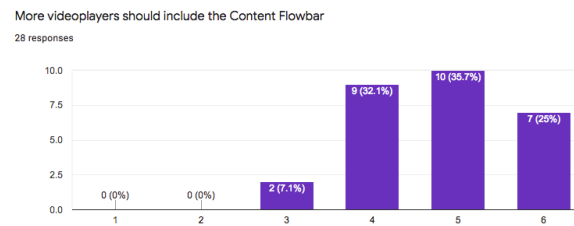


**Figure 7:** Keywords quality ratings, with positive and negative valence. Scales from strongly disagree to strongly agree.

#### 1.4.1.2. Usability, issues and user satisfaction with the content flowbar

A few participants commented on having the same keyword in every segment of the video: “*if every chunk is associated with 'neural network' then the label stops being temporally associated and may as well be metadata for the video as a whole*”. Some participants noted how the flow bar did not always align well with the video player making selecting clips awkward. In particular, they had difficulties in determining the

exact start and end of video clips that they were trying to capture. Figure 8 shows the overall positive response that the content flowbar was a valuable and useful navigation and discovery tool.

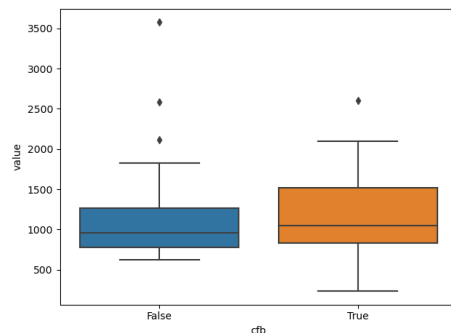


**Figure 8: CFB and videoplayer**

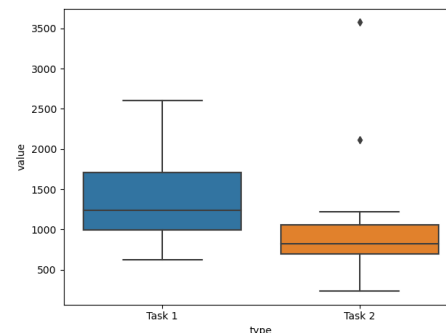
### 1.4.2 Analysis of the Interaction Log: preliminary results

In this section preliminary results from the interaction log analysis are presented. They are concerned with the performance of CFB, in terms of duration under different conditions. The log data of the participant's interactions was captured and compiled from the participant's sessions. To visualise the preliminary results, graphs were created using boxplots. These are presented in terms of the duration for the Content Flow Bar state (i.e. whether it was in use or not), and according to the order of the task (1<sup>st</sup> or 2<sup>nd</sup>), and subject topic of the task (i.e. Machine Learning or Climate Change).

**Performance of CFB:** Figures 9a and b show the boxplots for the (i) Duration by Content Flow Bar and (ii) Task order. The distributions of task duration for all participants were first plotted separately for CFB (on = with and off = without), and for the task order (first or second), Y axis is time in seconds.



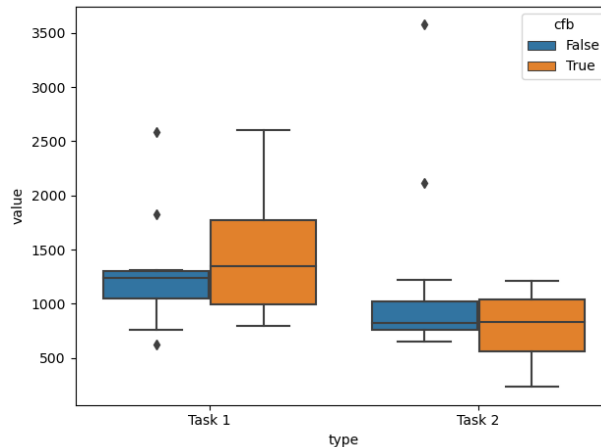
**Figure 9a: Boxplots for CFB**



**Figure 9b: Boxplots Task order**

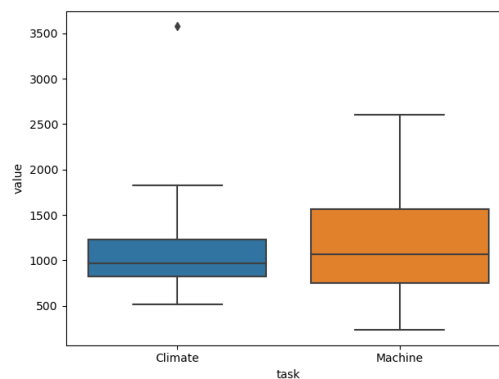
There seems to be a strong effect for task order, which is not unexpected in this kind of study due to training effects. The content flowbar was used for longer when used in the first task.

The distribution was then plotted taking into account task order, for CBF (on) and without CBF (off). Once task order is taken into account, the task duration and its distribution seems to deviate more strongly for when CFB is off (see Figure 10).



**Figure 10: Boxplots CFB x task order**

The distribution of task duration for Machine Learning and Climate Change was plotted again using boxplots, where the Y axis represents time in seconds (Figure 11). As can be seen, there is a difference between the two conditions, some participants seems to take more time to finish the Machine Learning tasks than when doing the task using the content flowbar. Hence, the log analysis has shown that participants quickly learn how to use the content flowbar over two tasks, suggesting it is easy to learn and use.



**Figure 11: Boxplots by task subject**

## 1.5 CONCLUSIONS AND FUTURE WORK

In the first section of this report, the design rationale for the content flowbar and the initial analyses from our user study has been presented describing the efficacy of using this novel interaction technique for supporting discoverability and enhancing navigation. Overall, the content flowbar was found to enhance early exploratory behaviour and information seeking and speed up searching for parts in a video where a topic was mentioned. It does this by providing visual cues about where in a video thumbnail to look for content that otherwise would not be perceptible. Our initial findings showed participants were able to discover information more easily. This suggests users can take more chances in following different paths to find the best match to their search, and also, importantly, eliminate irrelevant information more quickly.

Unfortunately, due to present Coronavirus context, our work plan and schedule had to be modified to accommodate all user studies over Zoom. It created specific problematic such as bandwidth and equipment available to participants, so the



sessions took longer. Consequently, results from the content flowbar could not be compiled and analysed in any depth in time for this report. Our plans for publication over the next few months include:

- To carry out a thematic analysis of the qualitative data
- To finish compiling the interaction log, including statistical analysis of results
- To establish the "ground truth" of wikifier's keywords, and validate the acceptability of this technique in our context.

## 2 X5MOODLE STUDY

Moodle is the most important Learning Management System in the world today. It is believed to be used by 80% of the universities, but also in schools. The total number of sites which it is deployed in exceeds 150,000 over 242 countries. Teachers use Moodle to interact with their students, by giving them access to resources, allowing interactive activities, extracting learning analytics and using it for grading purposes.

As part of the X5Gon project, a new tool X5Moodle was developed as a Moodle Plugin for accessing OCR educational and scientific material, including videos and articles (in pdf, docx, html... format). Students are not necessarily good at information seeking, they get lost or confused, or experience information overload, etc. A set of features to facilitate information retrieval and content navigation was thus developed. Besides providing a search engine, the tool provides additional ways of finding information, for example, through a recommender feature.

In order to assess the design of X5Moodle and its functionalities, X5Moodle was integrated in a specialised course at the Université de Nantes intended for Master students in Computer Science. To gather some feedback on the tool usage, we developed, and implemented analytics in X5Moodle. We then designed an exploratory user study combining the analytics with user feedback on usability, student interactions and experiences with the tool. In this report, we first present the pedagogical context of the study, then introduce the X5Moodle interface as seen from the students' perspective, followed by describing the assessment tools. Finally, we present and discuss results from the study.

### 2.1 X5MOODLE, THE PEDAGOGICAL CONTEXT

The course on Language models was developed and taught by Colin de la Higuera. It is part of the Masters course in Computer Science curriculum, with a specialisation in Machine Learning and Natural Language Processing. The course covers grammatical inference but also deep neural networks. The course started in September 2020 and lasted for 16 sessions of 1h 20 minutes each. There were 13 students participating in the course, half the students were based in Nantes, while the other half were based in le Mans.

The pedagogical goals for X5Moodle, in this course, were as follows:

- To get students to engage in something useful related to the course
- To allow them to explore and find extra material
- To allow them to help each other but not encourage laziness
- To be able to document the operation, the trials, the findings.

To meet the goals, students were given coursework, which was to be graded, and count for 10% of their final result. As it was the first time using X5Moodle in a real student learning context, it was tested and integrated into a course that the lecturer



felt that some prudence was warranted as to the state of X5Moodle and X5Gon resources. No tutorial on the usage of X5-Moodle was given.

The students were asked to do individual work on various themes relevant to the topic of the course. This work was exploration work: they could only perform well if they found extra material not delivered during the class. They were encouraged to use X5Moodle for this. In the report they were to submit by November 30<sup>th</sup>, they were supposed to add one small section explaining what they had found and how they had found it.

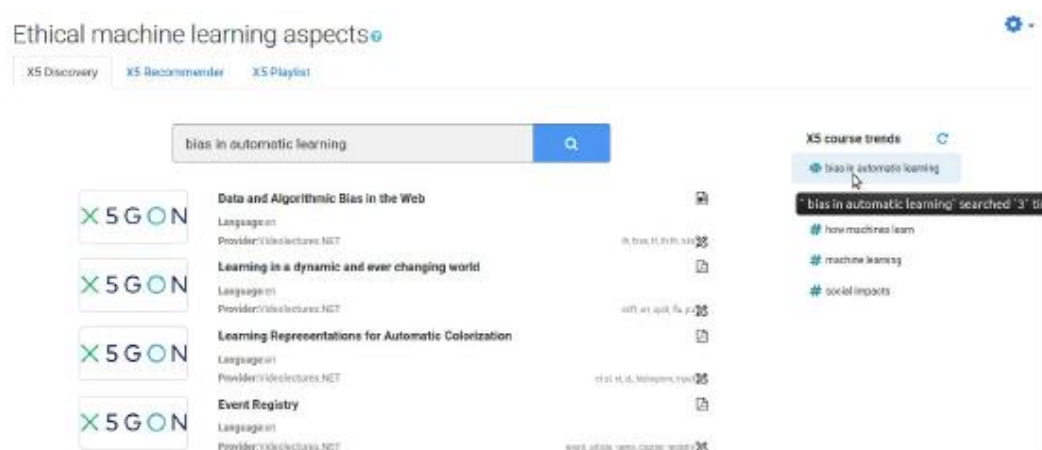
## 2.2 X5MOODLE USER INTERFACE AND FUNCTIONALITIES

X5Moodle has been developed with the Moodle environment in mind, containing specific functionalities with the user interface designed for teachers and students. Teachers developing courses in Moodle can add a new X5GON activity. This tool comes in three variants:

- X5-Discovery,
- X5-Recommend
- X5-Playlist

Teachers can choose which of the three variants they shared with students. X5-Discovery and X5-Recommend have the same functionalities for students and teachers. However, teachers have to build their playlists first from X5learn.org (see Report 9.3), as a list of links to X5Gon videos and pdfs for the course.

Once the X5-GON activity is installed within a course, a student from that class can then search resources using one of three settings if available. X5-Discovery provides the possibility to use X5GON search engine, which students will use it to find a new OER that will return a list of results (see Figure 12) from the X5Gon platform. Instead of searching by keywords, students can access the most popular search “**trends**” made by their fellow students. Trends thus can give students an alternative starting point based on what other students have been searching. Trends are updated and vary in function depending on the students' searches.

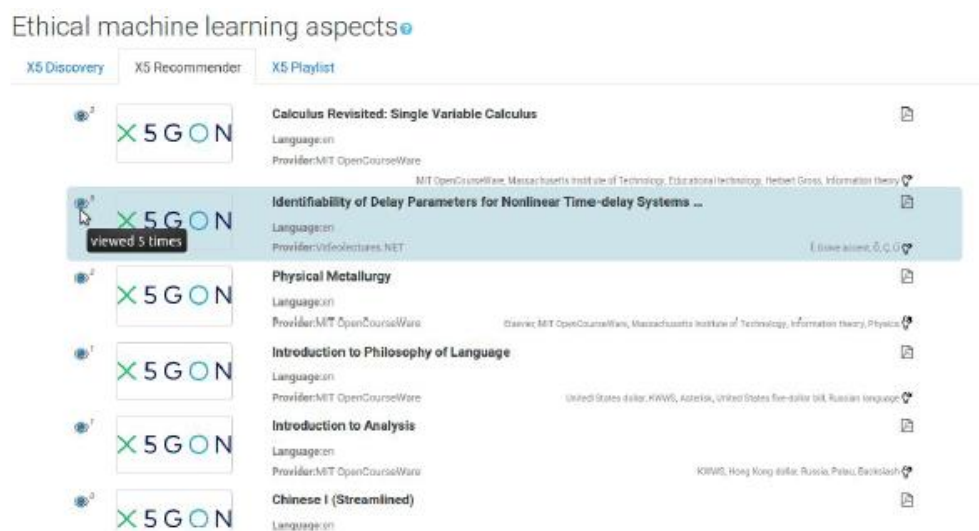


**Figure 12: X5 Discovery**

X5-Recommend was developed to complement for X5Discovery with the aim that students could find more interesting resources. It addresses the challenge of how to help students when using the internet navigation and search tools. It is well known that students can get overwhelmed by the number of references returned by search engines, and sometimes make random or poor decisions regarding the value of

which results to look at. The recommender function was designed to help alleviate this uncertainty. It can also give students access to OERs that would not have discovered by themselves.

The functionality of X5-Recommend is based on using the X5GON recommendation system that emphasises the history of the accessed resources (usage inside the course) to recommend new resources related more to the overview of students' activities within the course. Starting from a previously recommended list and relying on the original X5-GON item-base recommendation system, a new richer set of OER is built representing the initial list neighbourhood. A 'trendiness' score is then computed for these, based on their access history with weighing more the recent accessed ones, and implicitly based on the most viewed ones. Finally, the final score of an OER, used to build the new recommendation list, is computed using the trendiness score weighted by its distance towards others to assure the novelty and renewal aspects. The recommendations are systematically updated based on what each student explores but also as the classroom shifts its attention to searching for other new OERs (see Figure 13).



**Figure 13: X5-Recommend**

With X5-Playlist the student can access the different OER previously selected by the teacher. The number of accesses is registered, giving teachers valuable data concerning the extra material viewed by their students (see Figure 14).

## Ethical machine learning aspects

X5 Discovery

X5 Recommender

X5 Playlist

The screenshot displays a 'Teacher's playlist' on the X5GON platform. It features a list of video lectures with the following details:

- Groundwater Modeling with Machine Learning Techniques:** Ljubljana Polje A...  
Author: Jurem Kenda  
Provider: Videolectures.NET
- How Machine Learning has Finally Solved Wanamakers Dilemma**  
Author: Oliver Downes  
Provider: Videolectures.NET
- Robots learning from human teachers**  
Author: Andrea Thomaz  
Provider: Videolectures.NET
- Machine Learning for Prognostics and Health Management - Challenges and...**  
Author: Raj Bhattacharya  
Provider: Videolectures.NET
- 8 The Many Agents Around / I vari agenti in giro**  
Author: ...  
Provider: University of Bologna Digital Library

Each entry includes a thumbnail image, a title, author, provider, and a list of keywords. A 'Concepts' button is visible on the right side of the interface.

**Figure 14: Teacher's playlist**

As can be seen in Figure 15, for all results listed from X5Moodle tools, students can access additional information and references, like keywords to concepts. Keywords (5) are extracted based on their frequency inside the OER, offset by their frequency in the rest of the corpus OERs.

A concept (6) is a term (single or multi-words) semantically linked to the material. It is detected based on the Wikipedia concepts graph in which each concept is represented by a Wikipedia web page. Thus, the results list provided some hints about the results: the most 5 important keywords (6) and concepts (5), document type (video or pdf) (4) as well as the number of views (1), language (2), and the providers (3).



**Figure 15. Close up of results visualisation**

### 2.3. IN THE WLD STUDY

To evaluate how students used the new X5Moodle tool we conducted a classroom study. The goal was to assess the effectiveness and impact of X5Moodle on how students used the Moodle tool when studying and completing the coursework. It also enabled us to more fully investigate how X5Moodle integrated within the Moodle platform provided novel ways to support information seeking, and whether it changed how students learn and study. Opportunities were created, an intervention deployed, and different ways of behaving encouraged. We used analytics to assess tool usage and gathered further insights from the students' experiences with the tool.

### 2.3.1 Analytics

The use of analytics enabled us to investigate X5Moodle tool usage by grounding it in evidence. The kind of analytics we employed was interaction data, usage patterns, and performance.

At the most basic level, we wanted to capture data on which components of the X5Moodle tool students used. A core metric we used was usefulness which is “*the degree to which a product enables a user to achieve his or her goals and is an assessment of the user's willingness to use the product at all*”. We calculated the total amount of time each feature is used and the frequency of use. We also compared tool usages for X5 Discovery and Recommend.

Metrics from X5Moodle gave us opportunities to discover if the tool was functioning as intended. Moreover, it provided insights on which features are the most helpful or popular. Additionally, we wanted to get some feedback on how effective the X5Moodle interface design was; whether the provision of X5Moodle facilitated information seeking and helped students to fulfil their tasks. We also were also interested in assessing the breadth or diversity of X5Gon content and its relevance to student tasks by analysing data on their media consumption (e.g. types of references accessed).

By generating usage profiles, further analytics were derived to look at students' behaviour in more depth. We also investigated the distribution and variations of X5Moodle components overtime and their sequencing to establish patterns regarding the order in which components are used.

The X5Moodle analytics process consisted of measurement, collection, analysis, and reporting. We thus needed to define key metrics and indicators to capture relevant raw data, then process and aggregate these data for, analysing and visualising results. Table 1 shows the analytics used in terms of metrics.

Categories	Metrics
Feature Usages	Total number of times that a feature is accessed: <ul style="list-style-type: none"> <li>• X5 Discovery, X5 Recommender, Trends</li> </ul> Total number of times that a feature is used: <ul style="list-style-type: none"> <li>• Search (Discovery)</li> <li>• Concepts</li> <li>• Keywords</li> </ul>
Media Consumption	% video and % pdf accessed Total number of resources (or references accessed) Total number of unique references accessed % of resources accessed from X5 Discovery, X5 Recommender, % of resources accessed from elsewhere Keywords
Time spent on X5Moodle	Average time spend on the resource Average time spend on X5 Discovery, X5 Recommender, and elsewhere
Diversity & Usefulness of X5Gon	Total Number of individual references generated List of References Accessed List of References used in coursework Relevance of references for coursework
Students' behaviour	Adequateness of search Distribution of students usage

**Table 1:** The metrics used to analyse X5 Moodle functions and usage

### 2.3.2 Student's feedback

To collect insights about the students' experiences with and views about the tool during their course we designed and administered a questionnaire. We focused mainly on asking questions about the tool's usability: was X5Moodle easy to use and learn, untimely would design issues with the tool prevent usage? We also included the System Usability Scale (SUS) as part of the questionnaire. This is a simple, ten-item Likert Scale with five response options, participants can range statement from *Strongly agree* to *Strongly disagree*. Below are the ten statements on the system usability scale questionnaire (see Table 2).

<i>Likert Scale</i>	
<i>Strongly disagree</i>	<i>Strongly agree</i>
<ol style="list-style-type: none"> <li>1. I think that I would like to use this system frequently.</li> <li>2. I found the system unnecessarily complex.</li> <li>3. I thought the system was easy to use.</li> <li>4. I think that I would need the support of a technical person to be able to use this system.</li> <li>5. I found the various functions in this system were well integrated.</li> <li>6. I thought there was too much inconsistency in this system.</li> <li>7. I would imagine that most people would learn to use this system very quickly.</li> <li>8. I found the system very cumbersome to use.</li> <li>9. I felt very confident using the system.</li> <li>10. I needed to learn a lot of things before I could get going with this system.</li> </ol>	

Table 2: SUS Questionnaire

For the second part of the questionnaire, we developed open-ended questions to assess in more depth critical elements of X5Moodle, and to get further information about the students' experiences. The first question asked students to write an account their most striking impression of the tool. The next questions were intended to gather feedback on a novel aspect of the tool, namely X5 Recommender. The last questions were about how to improve the tool and/or design novel features.

The questionnaire was developed in French and implemented using the online Qualtrics tool but is given in English in this report. The set of open-ended questions were:

- Thinking about your experience with X5Moodle what was the most salient point? Please explain.
- Please list the most negative aspects /positive aspects of X5Moodle?
- There were a number of ways to find references, which one was the most interesting one, why?
- Was X5 Recommend helpful in finding references, why or why not?
- X5Moodle was developed to work within the context of a course rather than for an individual usage, what impact did that have on your experience? Explain.
- Do you have any suggestions to improve the X5 Moodle, such as conceptual or functionalities issues, or the user interface? Please describe in detail.

## 2.4. RESULTS

Overall, the students were positive about the tool. Both the analytics and the questionnaire data indicated that the recommender tool was used. However,

X5Moodle was not used as much as we expected. The following analysis examines why this might be so in terms of usage data.

### 2.4.1 Visualisation of analytics

The Jupyter notebooks were used to make the basic analytics starting from the raw data: cleaning them up and store in reusable data structures, allowing them to be visualized in different types of graphs (Pie, Bar...).

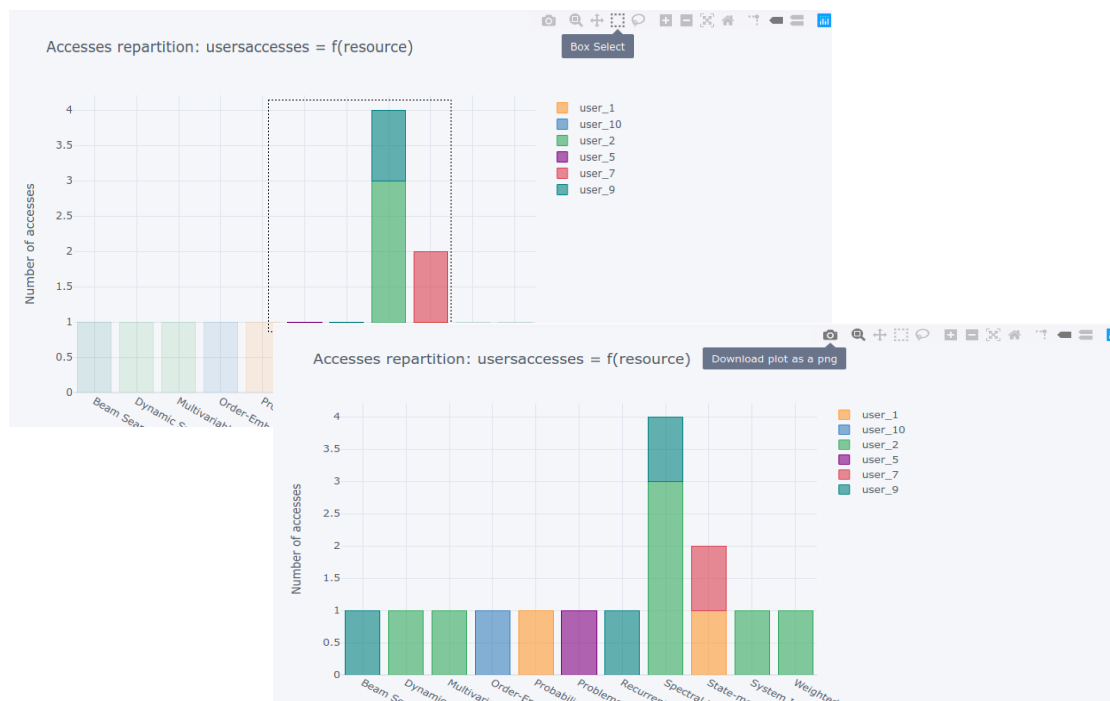
Basic questions are answered including:

- What are the resources seen by users? And how many times? Which are the most seen ones?
- Which are the most popular trends?
- What is the most important action done by users?
- Spread of the actions types per user?

The next step after the validation of these basic analytics was to implement them inside X5Moodle. The usage data was extracted and transformed into an interactive visualisation tool. This enabled both the researchers and lecturer to interact directly with graphs of the data more easily (see figure 16). Ultimately, such a tool can help teachers getting an overview of their courses and draw useful conclusions about potential learning issues that students could experience.

The interactive features comprise:

- Adding or subtracting elements, zooming in/ out,
- Making some annotations and downloading the graphs in the png format



**Figure 16:** Examples of graphs that can be used to visualise usage data.



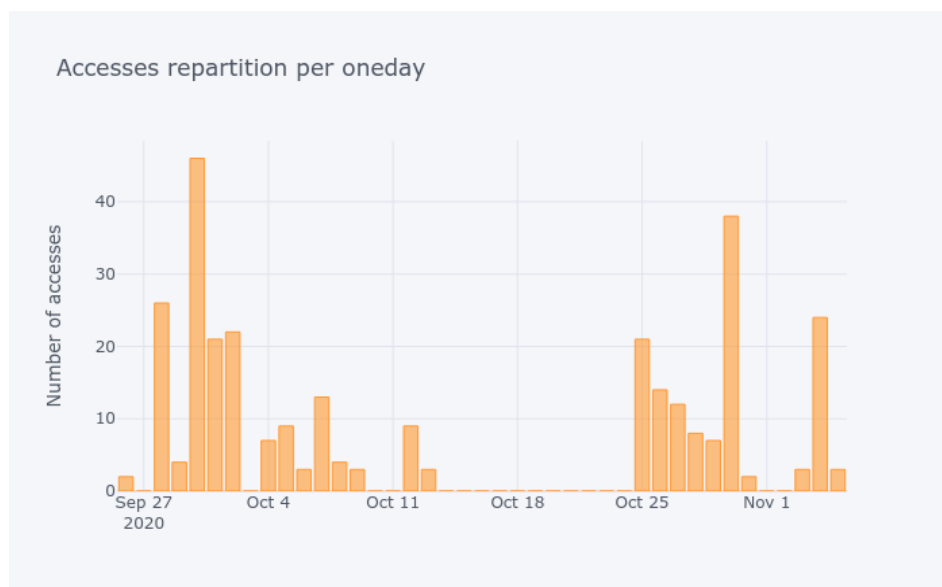
## 2.4.2 Analytics

The following graphs show some of the initial analytics derived to answer some of the questions that could be raised by a teacher during their lecture, and in a second stage, raise further research questions.

Since X5Moodle is a usage-driven AI tool, these basic graphs are based on the count number of users/students' actions inside the course: no personalized (specific user base) analysis nor individual traces or analytics were performed.

We label any type of user action (resource access, concept access....) or system event (computation of new recommendation, computation of new search results...) done inside the X5Moodle activity within a specific course as a 'trace'.

We describe the trace title or the event title of what event type is captured as an 'action' or 'action type'.



**Figure 17: Traces spread per day**

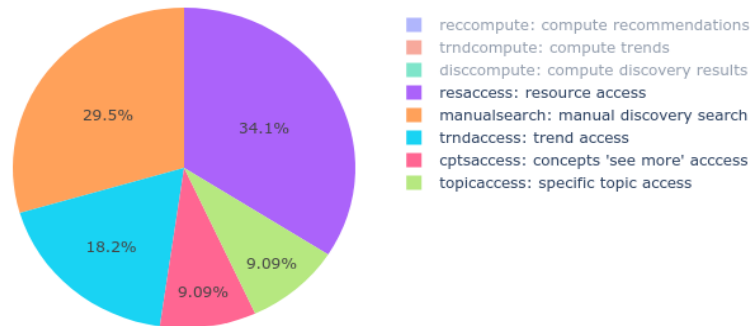
Figure 17 shows the temporal activity of students during their sessions. Here we are searching for a better way to represent the group activity over time, thus monitoring its productivity.

This will help the teacher to detect the most productive periods of their class, for example it will enable them to consider:

- Which are the most inactive periods? the beginning, middle or the end of the course?
- Connecting some special periods with teaching tasks or challenging concepts presentation, in the same periods, will help them to understand some behaviours and improve some learning aspects.
- Zooming on small periods (day, hour...) will help detect potential teaching issues in real time and enable them to intervene quickly to correct the direction the group is heading in, if needed



## X5Moodle traces repartition per action type



**Figure 18:** Traces repartition per action type.

Figure 18 shows the repartition of traces per action type. 9 possible action types are tracked:

- recompute, compute recommendations: system event describing the computation of a new recommendations list.
- trndcompute, compute trends: system event describing the computation of a new trends list.
- discompute, compute discovery results: system event describing the computation of new discovery list through using the X5GON search engine.
- resaccess, resource access: OER accessed and therefore, we assume consumed.
- manualsearch, manual discovery search: new search using the X5Discovery search engine.
- trndaccess, trend access: new search by choosing one of the top 10 trends.
- cptsaccess, concepts 'see more' access: 'see more topics' clicking to show more topics.
- keywrdsaccess, keywords 'see more' access: 'see more keywords' clicking to show more keywords.
- topicaccess, specific topic access: topic access.

The first 3 action types (disabled in Figure 6) are purely system events (launched, of course, by user actions) allowing to enable the 3 functionalities of X5Moodle: X5Discovery, X5Recommend and X5Trends.

⇒ 'Tracking these actions over time' could be a good indicator for a teacher to explain/interpret some students' strange/rare behaviours: for example, why most students are accessing a specific resource even if they are not covering all of the needed concepts...

This can be compared with a verification indicator of the quality of the delivered resources as well as the student choice explainability .

'resaccess' and 'trndaccess' proportions are very related to the 'manual search' proportion. In our estimation, since any learning scenario begins with searching new materials, those proportions mean to give us interesting insights about:

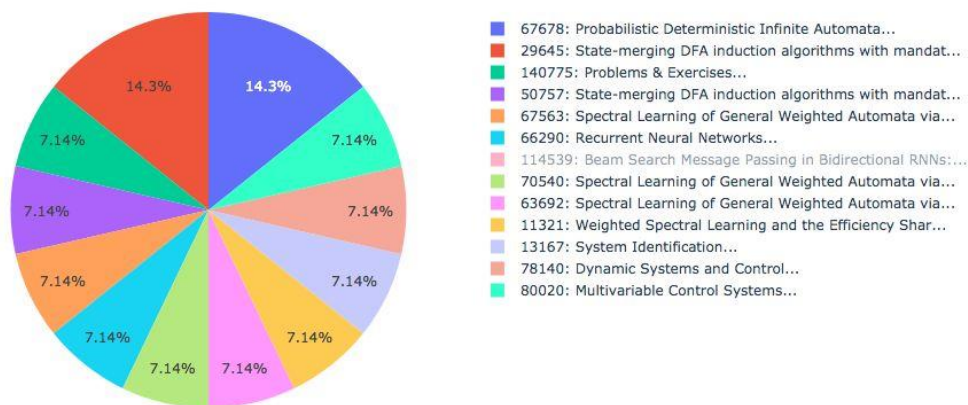
- How successful were the searches made by students? if the search is of good quality, many accessing/consuming resources traces will be followed.
- How efficient was using trends? thus the efficiency of the collaborating notion on the level of the learning process.

'topicaccess' proportion in relation with 'resaccess' proportion will lead us to know more about:

- Students mastery level of the seen learning concepts during their courses
- Are the provided resources clear enough (through the extra information shown: title, language...) to give students some thoughts about their contents?

'cptsaccess' and 'keywrdsaccess' will be a good indicator of what is the best way to represent a material: through semantic terms or frequency-base computed terms.

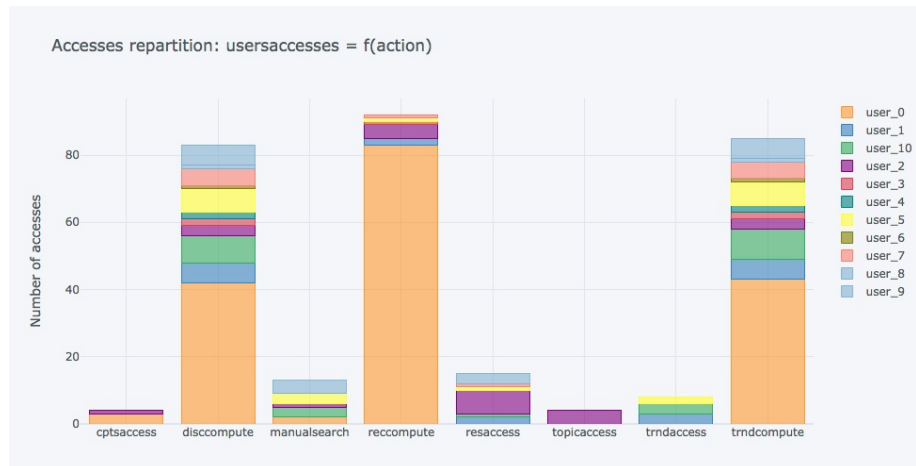
X5Moodle traces repartition per resource(OER)



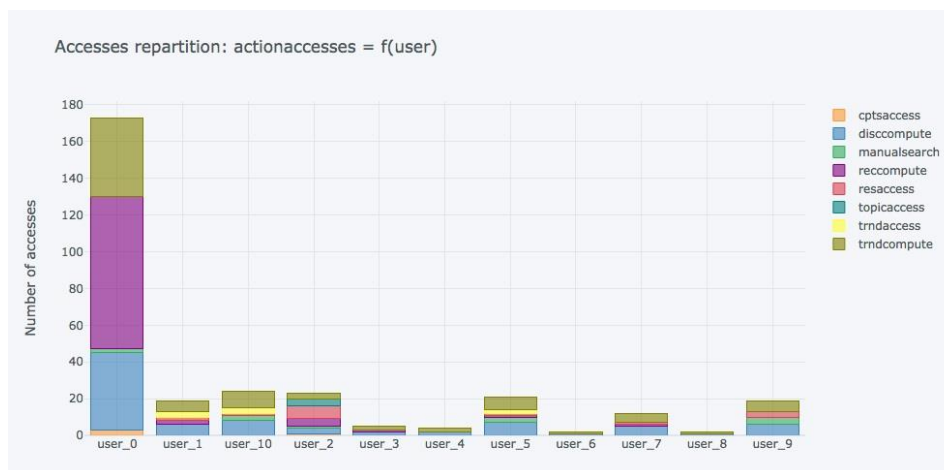
**Figure 19:** Traces repartition per resource.

Figure 19 shows the traces (especially 'resaccess' traces) repartition per resource(OER). Here we are seeking to give the teacher an interest map: indications about the materials on which students are focusing more. This will help to find answers to the following questions:

- Are the students following the same 'X5Playlist' set suggested by the teacher (could be visible from the beginning or kept hidden until the end of the course)?
- Why do some non-relevant resources keep merging while they are not very related to the course?



**Figure 20:** Users' traces repartition per action type.



**Figure 21:** Actions repartition per user.

Figures 20 and 21 represent the same analytic in 2 different ways: it is showing the repartition of traces per user and per action type.

In this case we want to detect potential targeted behaviours if needed. Because, indeed, the focus is on the usage traces to help students with the collaborative behaviour of the class, but we believe that some specific issues also deserve to be treated and not forgotten.

Representing the actions repartition by users will reveal if there are signs of:

- Inactivities or technical issues depriving students from progressing,
- overactivity misleading the main direction of the class.
- It could also be very helpful to monitor subgroup activities if the proposed pedagogical activity requires it.

In brief, these basic analytics meant to give teachers many helpful indicators regarding the class activity (thanks to the AI usage-driven tools used) that can help them improve a lot the learning process and detect some special behaviours (group or individual ones).

Adding to that, it will lead us to some future interesting perspectives about new advanced usage-driven analytics.

### 2.4.3 Questionnaire results

The questionnaire was administered on a voluntary basis and because of the low uptake of the course we ended up not getting any students filling it in. This was partly due to the number of students in this particular course being low and Covid onset, which seems to have affected students' behaviours negatively. Other possible reasons include:

- The exact role of the activity regarding the course was unclear: how the results would be measured in terms of grading was not sufficiently devised, probably because this was difficult to develop. This may correspond to a cultural issue: in France, they do not have the option of rewarding students with coupons and when some activity is not linked specifically with a grade increase, participation is often low.
- The interaction between the teacher and students was low: the organisation of the specific course had the lectures in September/October, but the activity was linked to their project which they delivered at the end of November. This meant that they were not seeing their teacher who couldn't, in turn encourage them in using X5-Moodle. It should be noted that in the individual report on their projects which 13 students sent in at the end of November 9 mention having used X5-Moodle, and only 2 of these give a short analysis of their usage. It is fair to say that they were disappointed, not by the tool itself but by the quantity of relevant resources (in comparison with what can be found on the web using a "normal" search engine).

## 2.5. CONCLUSIONS

X5Moodle worked well during the course. However, its uptake by the students was disappointing. Several reasons were put forward for this. We were also unable to get any questionnaire data so this meant we could not analyse the student's experiences of using it in any depth. In sum, X5Moodle's functions provide an alternative, more peer-based way of using a recommender approach to aid students searching for course material. The analytics, however, provided a useful resource for developing new visualisations for teachers to use to consider how to run and change the structure of their classes to keep students on track and help where they seem to be distracted or not using the resources in the way envisioned.

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