AI4T
AI FOR TEACHERS

Work Package 1:

Experimentation

Deliverable D1.3

Analysis of traces of use

“Methodological Framework For Data Collection and Learning Analysis”

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ABSTRACT	This report describes the collection of teachers' online learning traces, the proposed **Learning Analytics** for the collected data and the parsing of the learning analytics results in the AI4T project. This report firstly explains the current status of online learning in the AI4T project and the necessity and advantages of using learning analytics; secondly, it explains the workflow of the collaborative workgroups in AI4T and the data transfer in the process, showing the collection of data from the five countries and the data model proposed to adapt to this and the corresponding processing of the log files;Thirdly, it proposes a learning analytics methodology to be used on the collected data, i.e., **Descriptive Cards Mining** methodology, explains the definition of descriptive cards and the selection and definition of the relevant component **Indicators**, and describes the steps of descriptive card mining.Finally it shows the results of the descriptive cards mined from the data for each country, with comparisons and analyses, and shows the results of the global analysis.
KEYWORDS	Trace collection, Learning Analytics, Indicators,Descriptive Card

Dissemination level		
PU	Public	**X**
PP	Restricted to project partner (including the Commission)	
RE	Restricted to a group defined by the consortium (including the Commission)	
CO	Confidential, only for members of the consortium (including the Commission)	

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Introduction

The purpose of the AI4T (Artificial Intelligence for and by Teachers) project is to promote the use of artificial intelligence tools across Europe. Coordinated by France Education International, the project involves collaboration with the Ministries of Education, public institutions, research centers, private universities, and partners from five European countries: **France, Ireland, Italy, Luxembourg, and Slovenia**.

In this project, a series of online courses were designed to train teachers in the widespread use of artificial intelligence and were published on different online platforms in the five European countries, complementing face-to-face training and online seminars. The first two years of the project were successfully completed in February 2023 with the implementation of those training resources in all five countries. Nearly **500 teachers** took part in the trial phase by following the professional training pathway.

The project is based on the development of training in the use of AI tools for secondary school teachers - designed on the basis of the **Class'Code de l'AI MOOC** from the French National Institute for Research in Computer Science and Control (INRIA), who are part of the team in charge of the Training architecture and resources leaded by the University of Nantes. The resources created by the INRIA were then adapted by and enriched based on the needs and experiences of the participants, as well as on the testing and use of digital teaching resources incorporating AI bricks offered by various publishers. This resource is available on the project website in the 5 languages of the partnership. This deliverable was led by the partner INRIA.

The course includes 4 modules:

The Module 1 "Using AI in education" allow teachers to:

- Illustrate the general concern about AI in education.
- Raise questioning in each teacher's own practices with a simple interactive activity.
- Point out the AI-related challenges in education and core competencies required in the AI era.
- Discover the functionalities of some tools for experimentation.

The Module 2 "What is meant by AI?" content round on the following aspects:

- What AI is really, its potential and limitations for education.
- Present the diverse definitions of AI and its scientific fields.
- Experiment the basics of AI and its limitations.
- Explain where AI comes from.
- List the bricks at the origin of 3 AI-based applications: Natural Interaction, Image Recognition and Autonomous Car.
- List the existing AI techniques, what are their potential or existing uses in Education.

The Module 3 "How does AI work?" aims to:

- See how AI works.
- Get a first understanding of AI types.
- Identify AI approaches and how they relate to each other.
- Get a first understanding of what are data and how they are used.
- Experiment how machine learning and program training works and test the importance of properly prepared data sets.
- Understand how does an artificial neural networks work?
- Identify the different biases risks.

The Module 4 "AI at our service as teachers?" intends to allow teachers to:

- Understand how decision-making tools change practices or can improve them and have to be questioned.
- Understand what can be done with AI raising feasibility and ethics issues (questioning).
- Understand the impact of using decision-making AI tools and the necessary precaution of use.
- Be aware that too many tools can lead to a mental overload (for AI as for all digital tools)
- Identify some specific AI software for use in Education.
- Use of the Template for AI Characterization to analyse an AI software tool.

The concluding part of the AI4T MOOC is dedicated to:

- Presentation the future of education (an interview with one of the project promoters - Alain Thillay).

- Introduce the Textbook.
- Discuss Generative AI.

Led and coordinated by the LORIA team, the partnership collected **tracking data** from teachers during their professional training pathway, specifically during their online learning in the use of the online course (MOOC). By deeply analyzing these data, we can discover users' preferences and learning situations. This analysis complements the participants' feedbacks, collected through surveys and interviews, about the entirety of the professional learning pathway. The detail of this workflow will be explained in subsection 2.1.

In the framework of the professional training pathway offered to teachers in AI4T, an additional educational resource to the MOOC was coordinated by the University of Nantes. The textbook **"AI for Teachers, An Open Textbook"** has been translated into 5 languages: English, French, German, Italian and Slovenian. The first version of the textbook covers six areas and addresses the context of AI, which is becoming one of the most important areas to be aware of and to take into account in education. It is presented in 6 modules whose objectives are linked to the general training pathway aims. Therefore, the following description of its content reflects this purpose.

Module 1 “Why Learn About AI”

Lays out the reasons for learning about AI, along with a brief introduction to AI and the historical timeline of AI techniques. The reasons address both those who are afraid of AI and those who are convinced of its advantages.

Module 2 “Finding Information”

Addresses search engines, available options and settings, and a brief overview of how search works. Behind the Lens touches on the ethics of search and the business model of search engines.

Module 3 “Managing Learning”

Starts with the 2 common examples of Moodle with ML add-ons and Google Classroom: on to LA, EDM and scheduling and then the technical and ethical aspects of data handling.

Module 4 "Personalizing Learning"

Starting with the general idea of personalization and technology assisted personalized learning, we take up ALS (mostly ITS) and then use YouTube recommenders and models to explain how an ALS works. The flip side of ALS discusses some potential problems of overuse thus leading to collob. Learning which includes clustering.

Module 5 "Speaking, Listening and Writing".

Language is something which AI is getting good at. And language is also a key element in education. This module explains why AI is good at language and visits a number of language linked tools whose impact on education is important.

Module 6 "The Next Steps"

- Can AI play a creative role?
- AI going to change the way we teach?
- How to convince parents and collaborate with them

The Textbook is available on the project website: https://www.ai4t.eu/textbook/

References to online learning in this report refer to e-learning courses that are generated only based on the **AI4T MOOC** distributed to different e-learning platforms in various countries.

In this line of thought, during the following report, the learning analysis for the AI4T project will be presented. By studying the traces of teachers, who are also users of online learning, we hope to get answers to the following questions:

1. How many teachers have completed the training? How much did they complete?
2. How much did teachers participate? How much effort and time did they spend?
3. How willing were teachers to explore different content?
4. Which parts of the different sections and information were they more interested in?
5. How well do teachers perform in activities and questioning?

6. What kind of activities are teachers more willing to participate in?
7. What content are teachers more willing to give feedback on?
8. Are teachers participating in the training regularly? If irregular, at what times are they generally concentrated?

In order to tackle these questions, we had to collect data purposefully, propose a data model and form a dataset based on the characteristics of the data, propose data analysis and learning analytics algorithms based on the dataset and finally answer the above questions based on the results obtained from the algorithms. The **aim** of this report is to explore how the AI4T project is bringing new insights and impact to education analytics by analysing teacher user tracking data. Specifically, the subsequent sections of this paper will be organized around the following questions:

- Why do we need to use learning analytics?
- How to collect and process user tracking data of teachers in different online platform courses in multiple countries?
- What trends and patterns do we want to discover by processing and analysing this data? How do we discover these results? How can we improve the interpretability of these results?
- What results did we get and what are the implications of these findings for educational analyses?

To answer these questions, in the **Section 1 - Background**, this paper will provide an overview of the development and challenges of online learning, as well as how the application of learning analytic and data mining are utilized in education to address the issues. In the **Section 2 - Data collection**, we will discuss the challenges faced in the workflow and data collection of the AI4T project and present the collected datasets and the required tasks. Then, in the **Section 3 - Methodology,** we propose our methodology Descriptive Card Mining for processing and analysing the learning traces. Finally, in the **Section 4 - Results**, we present the results of the analysis, which is the Descriptive Card, and their impact on educational analysis and discuss practical applications and future research directions. We will conclude with **Section 5 Conclusion** that summarizes the problems and challenges we encountered, how we might tackle similar problems in the future and what we might try for better result in the future.

1. Background

Why do we need to use learning analytics?

In this section, we will first review the online learning and its challenges to then, discuss the application of learning analytics and data mining in education as a solution for these challenges. Next, we will introduce the workflow of the AI4T project showing how the different research teams collaborate in the tasks and the challenges we encountered during data collection. Finally, we will present the collected datasets.

1.1. Online learning: What is it and what challenges it brings.

With the rapid development of Internet technology over the past few years, online learning has gradually become a popular form of education. Online learning is an educational approach that provides educational resources and learning materials through the Internet. The purpose of online learning is to give learners greater flexibility in time and space, allowing them to learn according to their needs and pace (Chen L., Chen P., Lin Z., 2020). Online learning can encompass various formats, such as synchronous classrooms, asynchronous courses, online webinars, and video tutorials.

In the AI4T, leaded by the Université of Nantes, in collaboration with the INRIA and the consortium partners, the *Work Package 2 - Training architecture and resources team* create the AI4T MOOC, which was distributed in the online learning platforms of each country in the national language. In this way, online learning has helped us to disseminate educational resources and make them more accessible to teachers in different countries. However, online learning also poses some problems such as **low learner motivation, lack of interaction, and lack of effective feedback.**

To address these issues and to examine the impact of online learning on the AI4T project, we used learning analytics and data mining techniques. By collecting and analyzing large amounts of online learning data, we were able to gain insight into teachers' behavior and preferences when receiving training, thus providing targeted recommendations for analyzing the impact of online learning on AI4T. At the same time, by mining the data, we can discover feedback from teachers on our training, which can provide experience and help with subsequent program updates and similar or related projects.

1.2. Learning Analysis: Why we need it in the AI4T project.

The application of learning analytics and data mining in the education field has achieved significant results. By collecting and analyzing learners' data, researchers can gain a better understanding of learners' behaviors, preferences, and needs, thereby providing targeted guidance and suggestions for educators (Romero C., Ventura S., 2020) and (Clow D., 2013). Over the past few years, learning analytics and data mining techniques have been widely applied in various educational scenarios, such as online courses, blended learning environments, and traditional classroom teaching.

The applications of learning analytics and data mining in education mainly include the following aspects: predicting learners' performance and grades, identifying difficulties learners may encounter during the learning process, evaluating the effectiveness of educational resources and teaching methods, and enhancing the interaction between educators and learners (Romero C., Ventura S., 2020) and (Clow D., 2013). By utilizing these techniques, educators can provide more personalized and targeted support for learners, thus improving teaching quality and learning outcomes.

In the **AI4T project**, learning analytics serves three purposes:

- Firstly, it addresses issues such as low learning motivation and lack of feedback in online learning by providing insights into teachers' learning behaviors, attention distribution, and other information patterns. This information is crucial for analyzing the impact of our training on participant teachers.
- Secondly, learning analytics helps to mitigate the problem of different countries presenting the same online learning resource in different ways. In the AI4T project, five countries use different online learning platforms, resulting in differences in the structure and format of the online learning courses. This leads to variations in the collected data and makes it difficult to generate general

reports. Our proposed learning analytics algorithm uses indicators to provide a more general and explainable way to present the results. The methodology, including the algorithm and indicators, will be presented in the Section 3.

- Finally, learning analytics helps to verify conclusions obtained through other ways. In the AI4T project, another work team, *Work Package 3 - Evaluation*, addresses the impact of the training using questionnaires from teachers. The results of learning analytics can be compared with their work, providing additional insight into the effectiveness of the training.

2. Data collection

How to collect and process user tracking data of teachers in different online platform courses in multiple countries?

In this section, we will introduce the workflow of the AI4T project and the challenges we encountered during data collection. Then, we will present the collected datasets and our task in the AI4T project.

2.1. Workflow in AI4T: Where do we collect the user tracking data?

Figure 1 below shows the general framework of the information collection in AI4T. It explains how *Work Package 1 - Experimentation, Work Package 2 - Training architecture and resources and Work Package 3 - Evaluation* working are three groups in AI4T, related to the online learning in this report. The framework also explains why traces of user activity on e-learning platforms are important to the AI4T project and what these data are used for. Regarding the workflow of the project, it can be described as follows. The project divided the participants into two subsets:

- A target subset (as the “intervention group” in the evaluation report) that received training from our AI4T project. Participants in the target subset were provided with access to the professional learning pathways, including common online learning materials for all countries (a Mooc and an open textbook) and guided learning organized by each country through webinars or face-to-face sessions.
- A control subset (as the “control group” in the evaluation report) that did not receive any training for comparison purposes.

When the experimentation was over and all teachers finished the online training, the trace of the online course was collected by e-learning platforms and sent to the *Work Package 1 - Experimentation team* with Anonymized user IDs for learning analysis. Participants in both the intervention and control group, have completed questionnaires at the beginning and the end of the experimentation. A subset of teachers from the intervention group was also interviewed after they engaged in the professional learning pathway. The Work Package 3 - Evaluation team will use the data collected to compare the two groups and evaluate the impact of the professional learning pathway on their knowledge, perceptions and use of AI. Participants' feedback on their engagement and satisfaction with the professional learning pathway are also collected. The two analyses through learning traces and participants' feedback are complementary and provide a detail picture of participants' behaviors in the professional learning pathway.

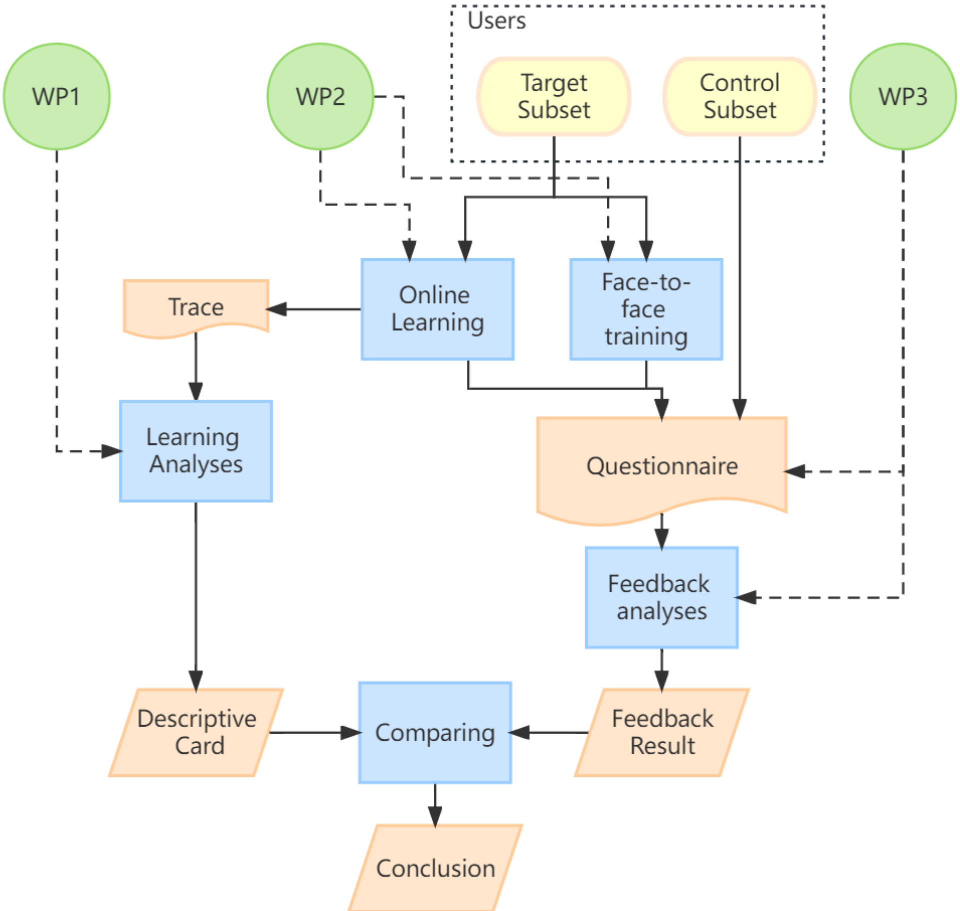

Figure 1: The general framework of AI4T related to Online learning and learning analyses. Related to Work Package 1 - Experimentation, Work Package 2 - Training architecture and resources and Work Package 3 – Evaluation.

In this process, neither group had access to the whole data to ensure the security of user data.

Figure 2 shows the data exchange between the e-Learning platform and the groups: *Work Package 2 (WP2) - Training architecture and resources* provided data of the AI4T MOOC resources to *Work Package 1 (WP1) - Experimentation*, the e-Learning platform provides *Work Package 1 - Experimentation* with **log files** of user behaviors after anonymising the user IDs, information about the online courses, and a table of the correspondence between the online courses and the resources of the MOOC. The *WP1* provides the results of the analyses after anonymising the user IDs to *WP2*. It then collects and cross-reference the user data itself but does not know the user behavior data. Such a process ensures that no group can correspond to a specific user by specific behavioral data, guaranteeing **data security.**

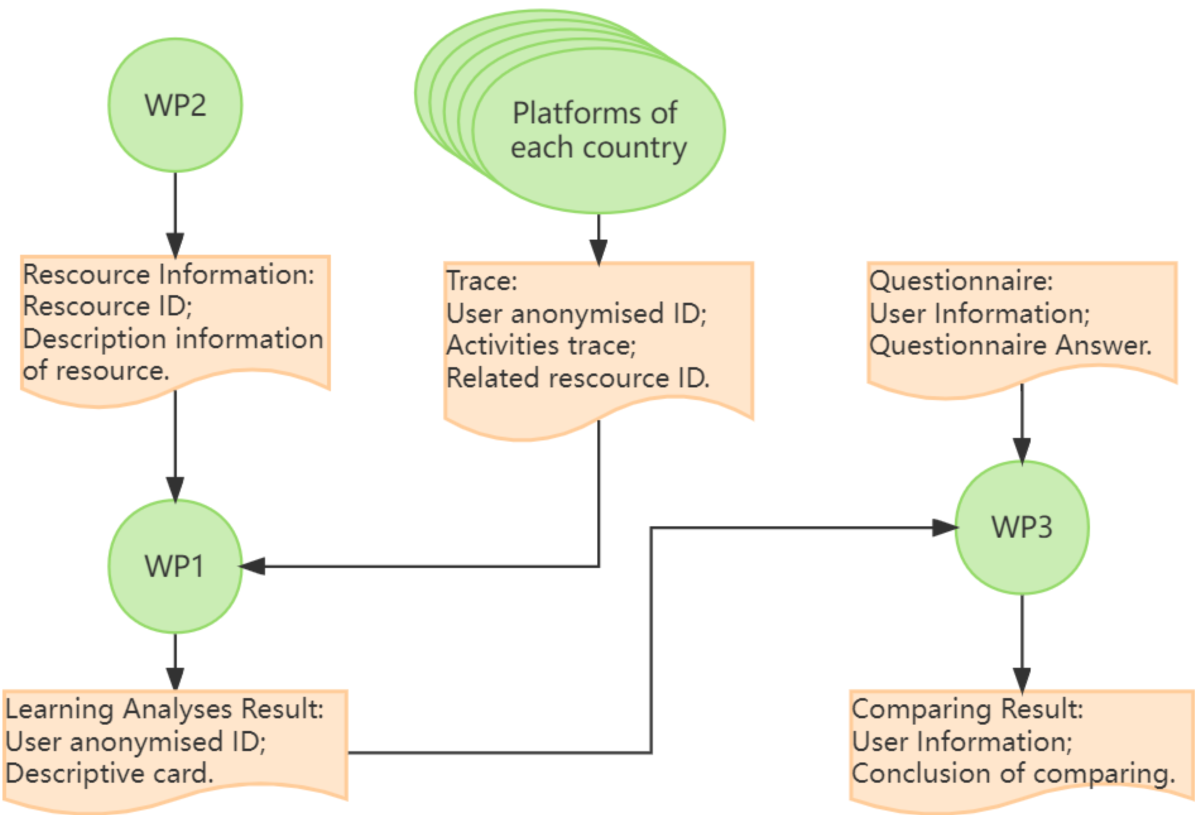

Figure 2: The data collect and exchange between the groups and e-learning platforms.

2.2. Data collection: Data model for trace with challenges and adaptation.

As mentioned in last section, for learning analytics, we obtained different information related to the AI4T MOOC: the resources and log files of user behaviors after anonymising user IDs, online course information, and a table of correspondences between online courses and MOOC resources from the e-learning platforms. To integrate these elements, we propose a data model consisting of a **user (NOUN) - behavior (VERB) - resource (OBJECT) structure** for recording user activities. Each row in the log file contains information about the user's ID, action description, and related resource ID. This means that:

- The user ID in this model should be a unique identifier given to the user by *Work Package 3 - Evaluation* during teacher selection, called as “The evaluation ID” and independent of the platform used. However, as we mentioned in the previous section, for data security reasons, we do not have access to the evaluation IDs and could not identify specify user.
- Therefore, during the learning analytics work, we used the IDs generated during the registration of the users assigned by the platforms in the different countries as the user ID, and all references to user IDs later in this report refer to this definition. In subsequent work, these user IDs will be matched with the evaluation IDs to ensure consistency of identification across platforms.
- The action description includes information such as the timestamp of the log, action type, and additional details like duration or grade. The action description is dependent on the log report obtained from different e-learning platforms used in different countries.
- The resource ID is a unique identifier assigned to the resource when the task designed the resource, independent of the platform or country.

However, collecting data posed several **challenges** for us. Firstly, different countries localized their online courses, adding their own learning resources, which resulted in differences not only in format but also in information. Secondly, different countries could use different methods for collecting log files, with France's e-learning platform using FUN-MOOC and the other four countries using Moodle. Even for those countries using Moodle, some used H5P for activities while others used SCORM, leading to differences in the action type, available grades, and other additional information. Thirdly, the date and the plan of the program and webinars were different for each country, which lead to the different for time-series. Finally, since the online courses were localized, the modules were structured differently, but the resources used were duplicated. Thus, we needed to collect the correspondence between the resource ID and the local resource ID to identify resources.

To address these challenges, we have taken three steps:

Firstly, we collected more data, including the correspondence between the xAPI file from the H5P plugin and the log file, and the correspondence between the resource ID and the local resource ID. Secondly, we filtered the data, to build a general data model and treated the additional local information as extended side information for the feature of the country. Finally, we applied our proposed learning analysis algorithm, to the general data model and side information to generate a report that includes a global analysis.

Having determined this data model, we created datasets for each country from the collected log files based on this model.

2.3. Data collected: Data sets consisting of log files obtained from different countries.

As described in the last section, we created datasets based on a data model consisting of a User (NOUN)-Behavior (VERB) - Resource (OBJECT) structure. In creating the dataset for each country, the central source is the log file that records the users. The dataset generated from the log files should be a flat table containing information such as user IDs, user behaviors and descriptions of the corresponding resources, with each row being a trace of one user behavior. However, in actual data collection, different countries may provide different log files to distinguish different behaviors or resources, or we may need to find the description information of resources based on the corresponding tables of online courses and MOOCs. In this section, we will focus on the basic information of the dataset built based on the collected log files, including the number of user behavior trajectories and the number of users collected, as well as what information is included and what is missing in the dataset composed of the information we collected for each country.

For instance, France used **Fun-Mooc** as an e-learning platform, log files for each relevant event are provided as xAPI format files, with different log files providing different behavioral categories, including 2,677 logs of users jumping from one page to another, 778 logs of users answering or navigating through questions, and 1,580 logs of users viewing and pausing videos. These data come from 140 users, and the information related to different events is described in different forms.

We integrated the above log tables by concatenating the "user_id" representing the user ID in the different logs for User (NOUN) in the data model and identifying Behavior (VERB) in the data model based on the category of the log file and the information within the log. We then identify and integrate Resource (OBJECT) in the data model based on the correspondence between the page information "page" and the block ID "block_id" with the "resource ID" of the MOOC. **For France, the final dataset with 5035 traces about 140 users was generated.**

As for the other countries, they have used **Moodle** as their e-learning platform, and the log files provide the following features for the generated dataset:

- “User ID”, which is the unique identifier for each user, used as User (NOUN) in the data model.
- “Timestamp”, which is the time at which the action was performed.
- “Event context”, which indicates the context in which the action was performed; “Component and Event name”, which are related to the type of action.
- “Description”, which describes the action and includes the user ID, action verb, and related resource ID.

The last three components are used to identify Behavior (VERB) in the data model by action verbs, and Resource (OBJECT) in the data model by associated resource IDs.

Unfortunately, due to some problems with the H5P plugin in Luxembourg and Ireland, many of the logs in these two countries do not recognize which are action verbs and are unable to generate the corresponding

Behavior (VERB). In the end, we were only able to label some of the logs with Behavior (VERB) by guessing some of the behaviors based on the resources of the user interactions in the logs. However, at least Ireland used the SCORM format instead of the H5P format for two of the activities, so we were still able to correctly identify the relevant data for these two activities.

At the same time, Slovenia and Luxembourg had another challenge. The localization of resources results in some of the online courses not corresponding to the resources in the MOOC, so it is not possible to identify this part of the Resource (OBJECT), and we are missing some of the data about the performance of the users in the quizzes and activities.

The final datasets of traces about users of each country are as shown in the table 1:

Country	Number of traces	Number of users
France	5035	140
Luxembourg	2182	23
Italy	64556	199
Ireland	2936	11
Slovenia	68619	162

Table 1. Numbers of logs and users collected from each country.

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3. Methodology

What trends and patterns do we want to discover by processing and analyzing this data?

How we discover these results?

How can we improve the interpretability of these results?

In order to address the challenges in online learning just mentioned; low learner motivation and lack of effective feedback, data processing and learning analytics are essential to represent the results of the AI4T project.

To represent the learning status of groups of users with common behaviors, we introduced the concept of **'Indicators'.** These indicators are calculated from selected subsets of features of the data and are used for measuring and reflecting different views of user behavior. The selection and definition of these indicators is not only based on current popular approaches to learning styles, but also helps to compensate for differences in datasets collected in different countries. Moreover it is relevant to our specific task, such as comparing the results of the WP3 questionnaire.

This section will be divided into two parts: firstly, we will present the data processing methods we used, which include the selection of indicators based on learning styles and learning tasks, as well as the definition of each indicator and the associated subset of features. Secondly, we will describe the learning analysis method we used, which involved clustering users into groups with common behavioral patterns and using the selected indicators to create a user profile for each cluster known as a **"Descriptive Card".**

3.1. Indicators selection: What trends and patterns do we want to discover?

In papers related to learning analytics (Treuillier, C., Anne B., 2021) and (Arnold, KE., Pistilli MD., 2012), the authors suggest that the four pillars of learning are attention, active participation, information feedback and daily consolidation. Therefore, we will select learning indicators around this theory. In paper “Student Engagement Predictions in an e-Learning System and Their Impact on Student Course Assessment Scores. Computational Intelligence and Neuroscience” (Hussain M., Zhu W., Zhang W., Abidi SMR., 2018), the authors state that a significant predictor of student achievement and risk in e-learning is student engagement, which in that paper is defined as the number, type, and frequency of students' participation in various activities and the associated statistical features extracted from their activity logs. In the paper “How to Quantify Student’s Regularity?” (Boroujeni MS., Sharma K., Kidziński Ł., Lucignano L., Dillenbourg P., 2016), the authors added the indicator of learning regularity, which is a very important indicator for long-term or cyclical online learning.

In the AI4T project, we select indicators to answer not only the requirement of *Work Package 3 - Evaluation*, but also the following questions, mentioned in section 0:

1. How many teachers have completed the training? How much did they complete?
2. How much did teachers participate? How much effort and time did they spend?
3. How willing were teachers to explore different content?
4. Which parts of the different sections and information were they more interested in?
5. How well do teachers perform in activities and questioning?
6. What kind of activities are teachers more willing to participate in?
7. What content are teachers more willing to give feedback on?
8. Are teachers participating in the training regularly? If irregular, at what times are they generally concentrated?

Based on this method (Treuillier C., Anne B., 2021) and the requirement from the Evaluation, we select the indicators as following:

Indicator	Meaning	Related question
Completion	Teachers' completion levels	1
Engagement	Teachers' actions taken and time spent	2
Curiosity	Teachers' desire to explore	3,4,6
Performance	Teachers' training outcome	5
Reactivity	Teachers' willingness to respond	6,7
Regularity	Teachers' persistence	8
Attention pattern	Distribution of teachers' attention on each module	4,6
Time pattern	Distribution pattern of teacher login dates	8

Table 2. Selected indicators and their meaning

It is worth noting that Attention Mode and Time Mode indicators are non-linear indicators, and we will show and analyse them graphically, while the other indicators are linear as well as numerical. For numerical indicators, we can more easily quantify how high or low the indicator is and show how good or bad the user performs in this indicator by using a value between [0-1]. During the learning analysis, users are cluster based on the linear numerical indicators and show each cluster by numerical hexagrams, the details of which will be presented in section 3.3. For the non-linear indicators, they are analyzed and presented graphically for each country.

3.2. Data processing: How could we discover the selected indicators from the raw data?

After receiving the raw date from all the 5 countries and generate the datasets based on the data model as mentioned in section 2.3, we used the selected indicators in the last section to process the collected data and extract the **related features** for each indicator. These features include three categories.

- The first group is raw features similar to "User ID", "Timestamp" and other raw features.
- The second group is similar to "Resource ID", "Module" and so on, which need to be extracted or found out from the raw data. For example, "Resource ID" needs to be extracted from the raw feature of "Description", while "Module" is based on the raw feature of the course. And "Module" is searched based on the correspondence table between the course information and the MOOC.
- The last group is calculated based on the statistical information of the previous two categories of features, similar to "Total time spent", "Rate of resource viewed ". For example, "Total time spent" is the total time spent in the course by the user according to the "User ID" to find out all the traces of the same user and then calculated according to the "Timestamp".

As we mentioned in Sections 2.2 and 2.3, there are different raw features in each country's dataset. Therefore, for the first and second groups of features, we should keep the common features and process the different features to ensure that we can compute the last group of features in the same way. Firstly, we retained features common to all countries' datasets. These include:

Features	Meaning	From
User ID	The id of user.	“User ID”
Action	The action taken by the user in this log.	Extracted from the “Component and Event name” and “Description”

Action type	The category to which the action belongs, include view page, doing quiz, doing activity and so on	Extracted from the "Component and Event name"
Resource ID	The id of the related resource.	Extracted from "Description"
Module	The module to which the resource belongs.	Inferred from the "Event context" in the log file and the correspondence file provided by the countries between the localized resource IDs and the resources ID in the original MOOC
Time	The timestamp of this log	"Timestamp"

Secondly, as mentioned before, we are dealing with different raw features in each country's dataset. The component with the greatest variation is the raw features that measure **user performance**. Since not all traces of quizzes and activities were collected for every country, the pass rates of quizzes and activities as common features were generalized. In the next learning analyses for different countries, we will add more features like correct rates if more data on quizzes and activities for that country are available.

Finally, we processed the above data by country and statistically calculated some new features to explain the indicators. **The indicators are so defined as following:**

Indicator	Related features
Completion	Rate of resource viewed
	Rate of quizzes answered
	Rate of activities participated

	Rate of module viewed
Engagement	Total number of actions
	Total time spent
	Number of activities or quizzes actions
	Time spent for activities or quizzes actions
	Number of pages viewed action
	Time spent for page viewed action
Curiosity	Number of different actions types teacher take
	Number of the action out of the MOOC
	Number of the action different from the general actions
	Average of number of pages viewed for each module
	Average of number of activities or quizzes for each module
	Average of time spent for each module
Performance	Rate of quizzes passed
	Variance of quizzes passed in each module
	Rate of activities passed
	Variance of activities passed in each module
Reactivity	Rate of modules that users are willing to view

	Rate of post-course quiz or activity that user willing to take in the module they are willing to view
	Average of delays in quizzes or activities after the view of the course
Regularity	Total number of days attended
	Number of days attended on training days
	Difference between the time spent per day and the average time spent by all users on that day
Attention pattern	Number of actions in each module
	Time spent in each module
Time pattern	Number of actions on each day
	Time spent on each day
	Frequent pattern from the sequence of the login date

3.3. Descriptive card: What kind of result we want to get and how to improve the interpretability of these results?

In the previous subsection 3.1 and 3.2, we explained how the use of selected indicators can help compensate for differences in datasets collected across diverse countries. As we have previously mentioned, using indicators in conducting analyses can also contribute to the provision of a more comprehensive and comprehensible way of presenting results. This is commonly referred to as the **"Descriptive Card" concept.**

A Descriptive Card constitutes a user profile that is established by clustering users who exhibit similar behavior patterns and share common characteristics. These patterns and characteristics are identified through the analysis of selected indicators, both of the linear and non-linear variety, that were previously discussed. To generate a Descriptive Card for a cluster of users, numeric indicators are computed by the features of the center of mass of the cluster, while non-numeric indicators are extracted through data analysis or pattern mining algorithms applying on the internal data of the cluster.

Descriptive Cards facilitate the presentation of results in a more intuitive format. As an illustration, in Figure 3, we present six numeric metrics in the form of a six-manifold star and the remaining two non-numeric metrics in the form of bar and line graphs.

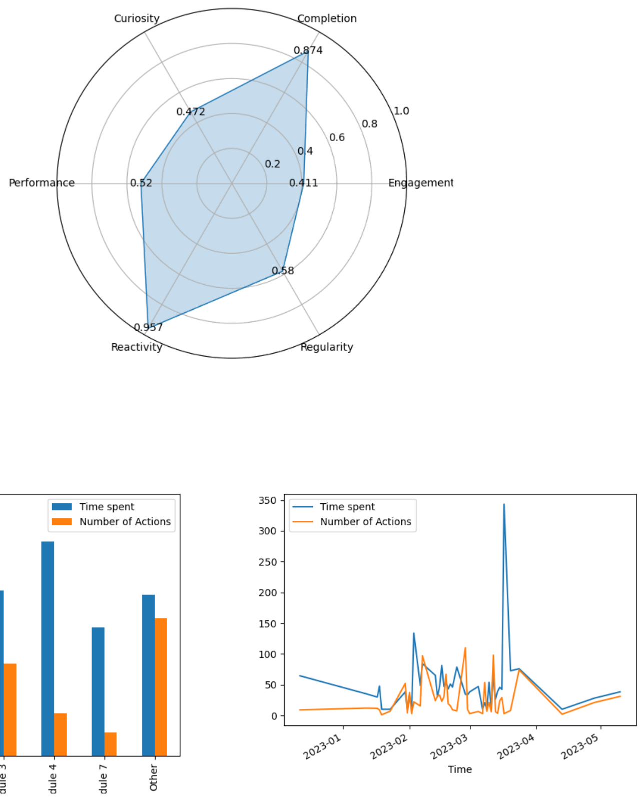

Figure 3. Descriptive Cards for a group of learners.

3.4. Framework of learning analysis and selected algorithms: How do we discover the descriptive card?

In the framework of the AI4T project, we proposed the Descriptive Card Mining as a specific framework for the learning analysis method and algorithms as shown in Figure 4.

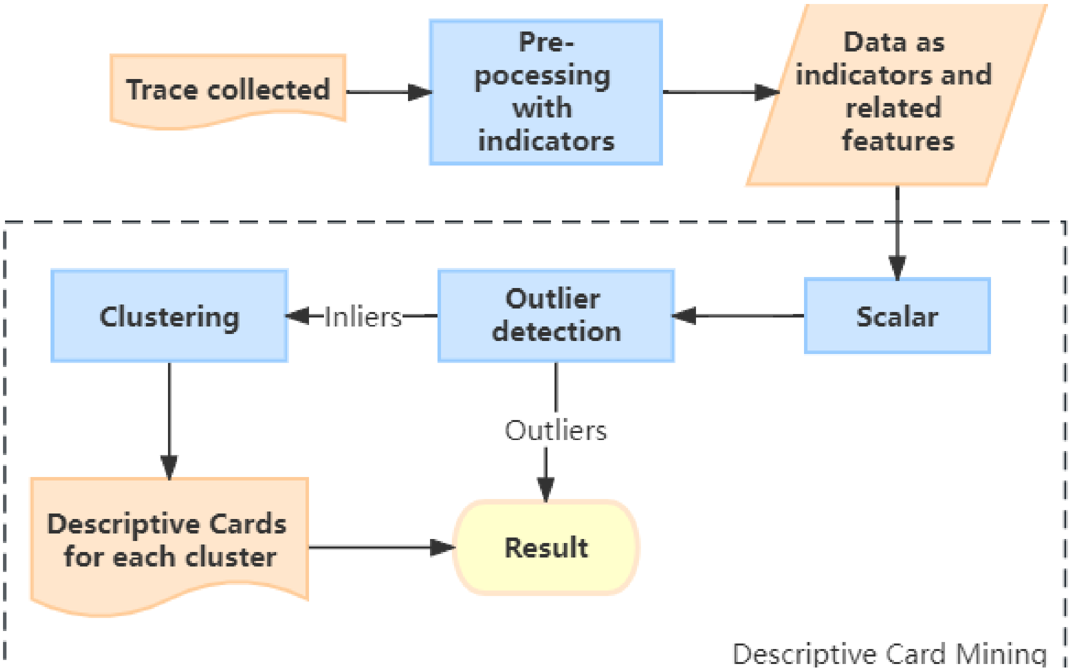

Figure 4. Framework of Descriptive Card Mining

After the data pre-processing, mentioned in the previous subsection 3.2, the first step of Descriptive Card Mining is **scaler for the data**. This is essential because the attributes are derived from various resources and exhibit dissimilar scales. Moreover, it is possible that some users may not be utilizing our online courses optimally or may be significantly different from the average user for other reasons, resulting in the presence of extreme values in the data. To address this issue, we use a standard scalarization in this step. It not only facilitates the detection of outliers, but also performs better in terms of clustering compared to other scalarization methods.

The second step is **outlier detection**, which help us to filter out users who exhibit extreme values and enhances the performance of clustering in the next step. Outliers are users who demonstrate atypical behaviors and may not be associated with any other users. However, it is worth noting that it is important to identify these non-standard users, as their atypical behavior may represent a cause for concern, so they need to be analysed differently. At the end we use indicators to describe them individually instead of categorizing them into a certain cluster. In this step, we use the **Isolation-Forest algorithm**, which is a popular choice for outlier detection.

The third step is **clustering**. Clustering is a technique used in data analysis that involves grouping similar data based on their inherent characteristics, in our case, it is the grouping of users who exhibit similar behavior patterns and have common characteristics. After outlier detection, clustering is at the heart of our learning analysis and is used to redefine user profiles. In this step, we choose **the K-means algorithm,** which is the most popular clustering algorithm. Note that in this framework, the previous steps are the same for all countries, while K-means is used to select different K-values for each country, from 2 to 10. The ASI (Average Profile Index) was used as a measure of performance for the different K-values and use it to determine the K-value that should be selected for each country's local data.

With a list of the best K values for each country, l_k[K1,K2...] , we also set the K values from min(l_k) to sum(l_k) to do K-means clustering for global learning analysis. Note that, for the small groups which the size is lower than the threshold (the threshold is set as 5), they will be treated as outliers and analysis later.

The final step is to **generate the Descriptive Card** for each cluster of users. In this step,the numeric and non-numeric indicators were separated. For numeric indicators, the features of the center of mass of the cluster to compute were used. The computation process is as follows: determine the center of mass C for the cluster, and then normalize the features of C. Subsequently, we obtain the final value of each indicator by calculating the average of the relevant subset of features for each numeric indicator. This method ensures that the resulting numeric indicators accurately represent the characteristics of the cluster and facilitates effective analysis and interpretation of the data.

4. Results

What results did we get and what are the implication

of these findings for educational analysis?

In this section we will first present the **Descriptive Cards** derived from analysing the data collected from each country. It will be followed by an analysis of what they have in common and what is different. Finally, the Descriptive Cards derived from analysing all the data globally are presented.

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4.1. Results of learning analysis: Descriptive Cards for each country

For each country, we show the results in two parts:

One part is the numerical indicators, which we show as a six-man star with the corresponding values of the six indicators as vertices. For example, the right images in Figure Fra-1, we show the results of analyzing six indicators for a group of teachers. The values of the indicators are in the range [0,1], with values closer to 1 indicating that the group of teachers is measuring the indicator better, and vice versa, indicating that the group of teachers is lacking in that indicator. In this expression, the area of the star can in turn reflect the quality of the training received by this group of teachers.

The other part is non-numeric indicators, which we represent with histograms and line graphs. The main purpose is to show the distribution of the user's attention through the time spent and the number of actions performed by the user. In general, the higher these two indicators are, the higher the user's attention is. For example, in Figure Fra-2, the left graph represents the distribution of user's attention to each module as a histogram, with the horizontal axis representing each module, the height of the blue squares on the vertical axis representing the time spent by the user on that module, and the height of the orange squares representing the number of operations recorded by the user on that module; the right graph represents the distribution of the user's attention over time, with the horizontal axis representing the date, the blue line representing the change of time that the user spends on online learning courses every day, and the orange line indicates the change in the average number of operations performed by the user per day.

France

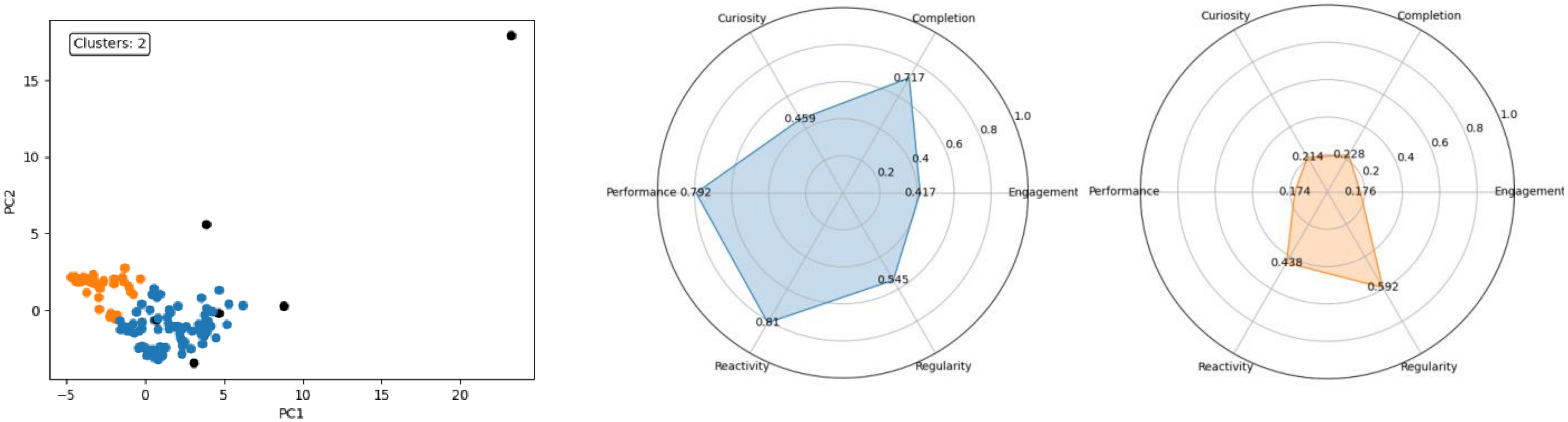


Figure Fra-1: Descriptive Card of France.

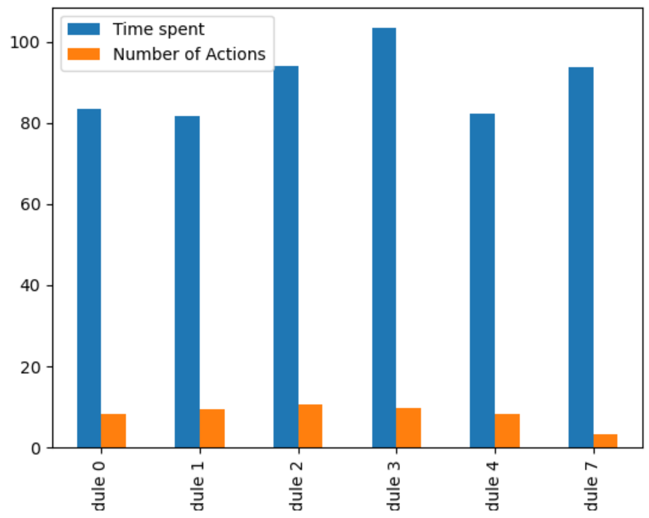
The left image shows the clustering result for users after visualization, and the right image shows the values of numerical indicators for the corresponding of the clusters in the left image.

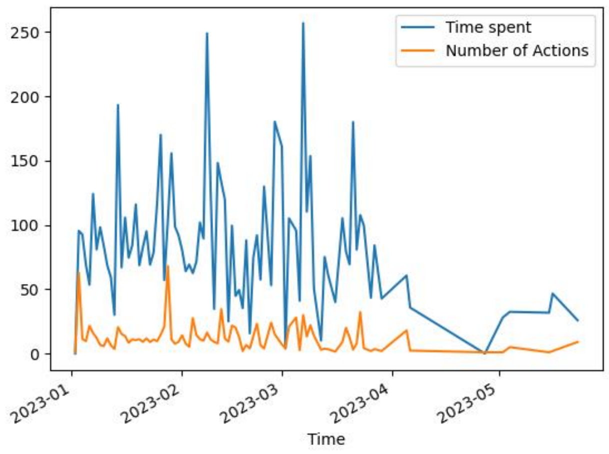
In the figure above (Figure Fra-1), we can see the results of Descriptive Card Mining on the French dataset.

In the image on the left, the outlier detection results show that out of the **140 users, 7 users** are difficult to be grouped in a certain category with the others and are labelled as black outlier data points; the clustering result show that the remaining users are clustered into two clusters and are identified as the cluster containing 82 blue data points and the cluster containing 51 orange data points. The images on the right shows the values of the numerical indicators for these two groups of users for the blue cluster and the orange cluster.

From this, it is clear that users in the blue cluster have higher values for most indicators than users in the orange cluster, except for the "Regularity" indicator. Especially in the "Performance" indicator, the difference is the largest, the average value of users in the blue cluster is as high as 0.792, while in the orange cluster it is only 0.174, while in the "Regularity" indicator, the difference is not large, with 0.545 and 0.592 respectively.

If we analyse the contribution of each feature to this clustering result through the correlation coefficient, we can find that the highest results are 0.75 for "Quizzes_Number" (representing the number of completed tests) and "Rate_Activity" (representing the rate of completed activities) and these two features belong to "Performance" and "Completion" indicators respectively.





Fra-2: non-numeric indicators for France.

The left image shows the distribution of user attention to each module; the right image shows the distribution of user attention over time.

In Figure Fra-2, we can see that **French users' attention distribution on each module is not very different**. Faced with different content, users seem to have no preference and desire to explore. This is part of the reason why users in the orange or blue clusters do not have high values on the "Curiosity" indicator, which are 0.45 and 0.21 respectively. At the same time, in French training arrangements, the promotion of online courses is a long-term regularity and is combined with other trainings. This allows us to see that over time, users' attention does not fluctuate much.

Italy

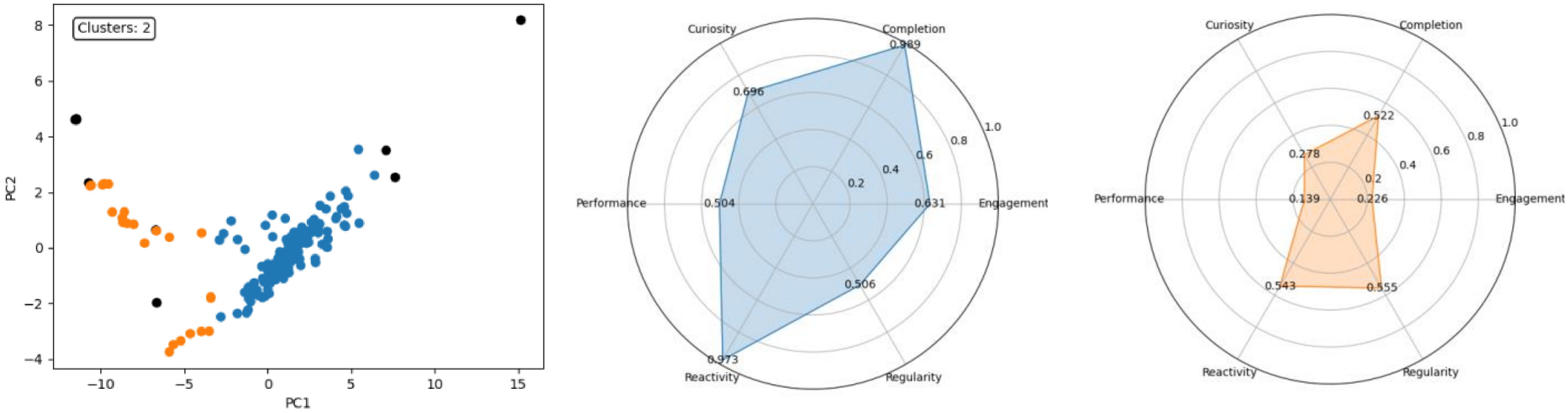


Figure Ita-1: Descriptive Card of Italy.

The left image shows the clustering result for users after visualization, and the right image shows the values of numerical indicators for the corresponding of the clusters in the left image.

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In Figure Ita-1, above, we can see the results of Descriptive Card Mining on the Italy dataset.

In the image on the left, the outlier detection results show that out of the **199 users, 10 users** are difficult to be grouped in a certain category with the others and are labelled as black outlier data points; the clustering result show that the remaining users are clustered into two clusters and are identified as the cluster containing 165 blue data points and the cluster containing 24 orange data points. The images on the right shows the values of the numerical indicators for these two groups of users for the blue cluster and the orange cluster.

We can see that **the results for Italy are very similar to those for France**, showing two clusters. In both cases, larger clusters exhibit higher learning metrics. Notably, **Italy has significantly more users in higher-performing groups** than in lower-performing groups. Italy differs from France in that the most significant differences are not in the "Performance" indicator, but in "Completion" (0.989 and 0.522) and "Reactivity" (0.973 and 0.543) of the respective clusters. When doing a correlation with the coefficient analysis on the characteristics of the Italian data set, there was no feature above 0.5 like France. It could be say that the difference between the two clusters comes from the overall trend of each feature.

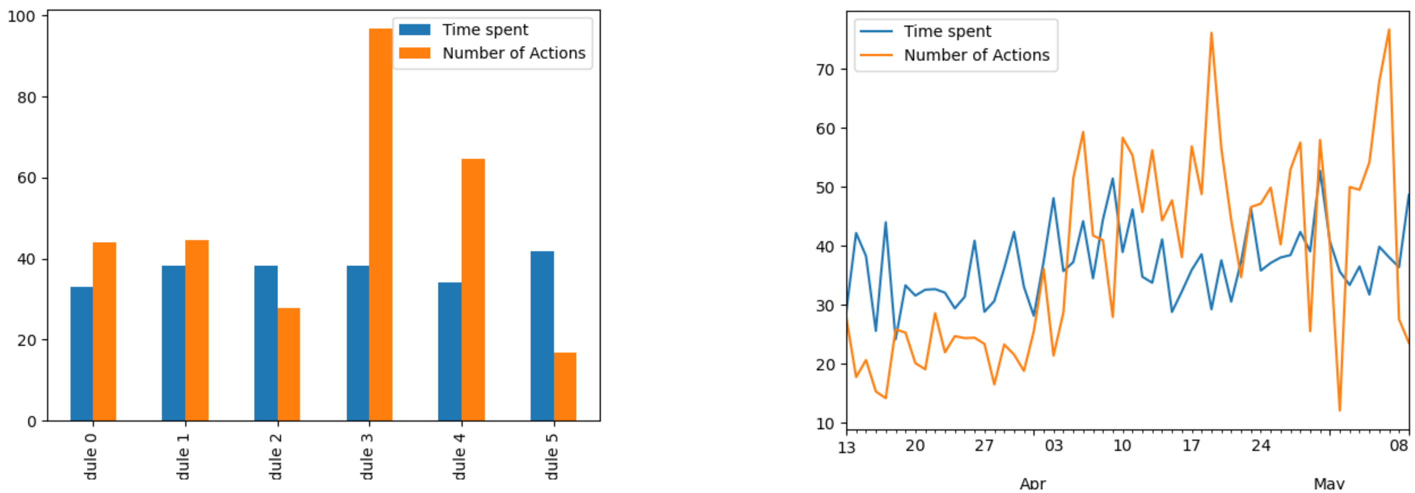


Figure Ita-2: non-numeric indicators for Italy

The left image shows the distribution of user attention to each module; the right image shows the distribution of user attention over time.

In Figure Ita-2, in the left image, we can see that although users spend almost the same amount of time on each module, **on Modules 3 and 4, users perform significantly more operations.** This may be due to the fact that 3 and 4 contain more interaction contents such as **quizzes or activities** after being localized in Italy. This can also be seen from the distribution of user attention in time in the right image. In Italy, MOOC courses introduce different modules to users in order. Modules 0-2 are introduced before April 3, and on April 3-17th is module 3-4, which corresponds to the peak period in the image on the right side of Figure Ita-2, especially when it reaches the highest on the 17th. It can be said that some image peaks after that were higher than those before April 3 due to users submitting their previous grades and making up for previously unfinished courses.

Slovenia

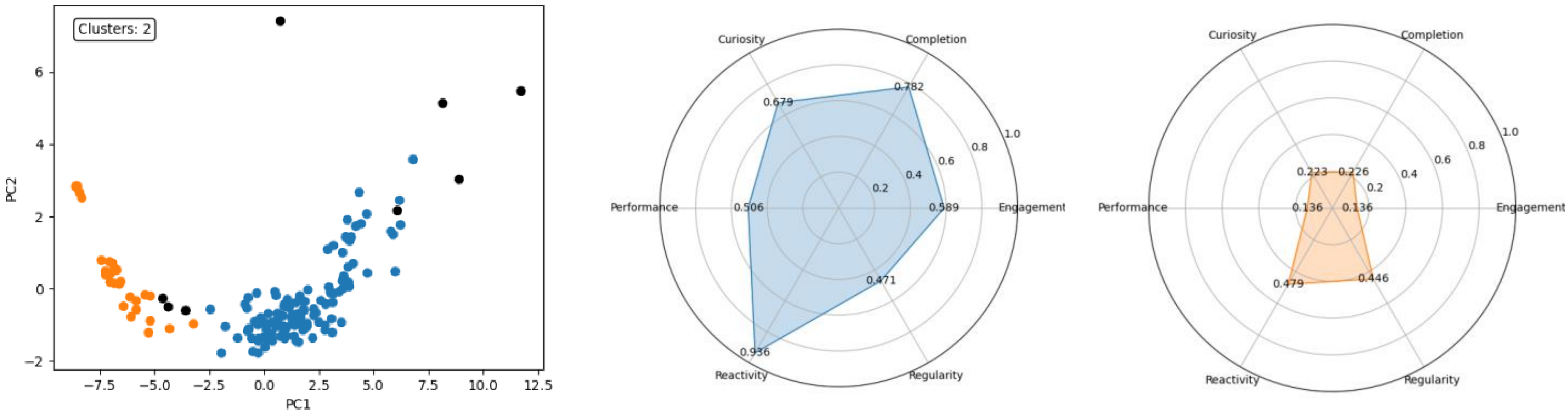
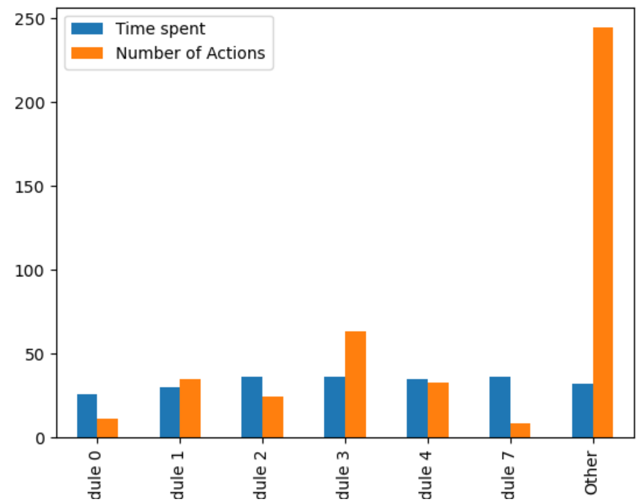


Figure Slo-1: Descriptive Card of Slovenia.

The left image shows the clustering result for users after visualization, and the right image shows the values of numerical indicators for the corresponding of the clusters in the left image.

In Figure Slo-1 showed above, it can be seen the results of Descriptive Card Mining on the Slovenia dataset. In the image on the left, the outlier detection results show that out of the **161 users, 8 users** are difficult to be grouped in a certain category with the others and are labelled as black outlier data points; the clustering result show that the remaining users are clustered into two clusters and are identified as the cluster containing 119 blue data points and the cluster containing 34 orange data points. The image on the right shows the values of the numerical indicators for these two groups of users for the blue cluster and the orange cluster. Although we lost some features of the Slovenian data, surprisingly **the results are highly similar to the Italian results**. The main differences between the two can only be seen from the following non-numeric indicators:



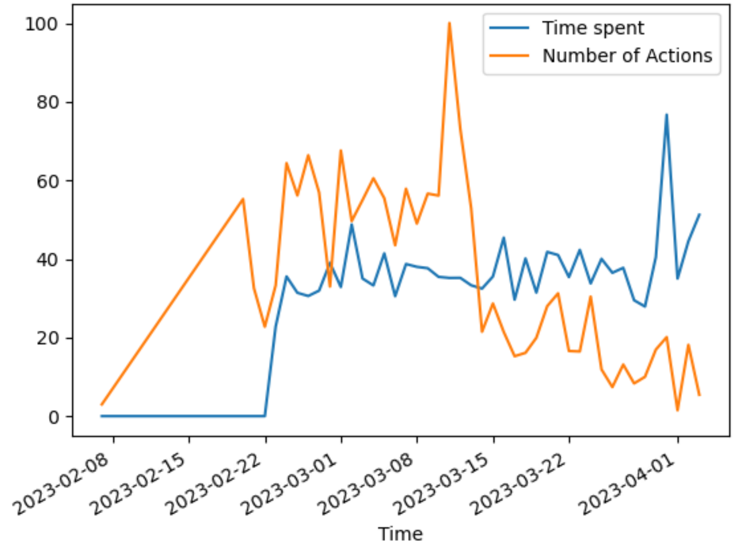


Figure Slo-2: non-numeric indicators for Slovenia.

The left image shows the distribution of user attention to each module; the right image shows the distribution of user attention over time.

In Figure Slo-2, in the left image **the distribution of user attention to each module of Slovenia is similar to Italy**, if we ignore the Module Other. The content in the module "Others" was designed by Slovenia itself. In order to maintain the comparability of analysis across countries and because there is not a comparable relationship between this part of the information and MOOC, when analyzing distribution of attention in each module it can only be listed separately (in the clustering step, we still took it into account). There are many user operations in this part. In future work, if we complete the unification of this part and MOOC, then this part of the data is also worthy of re-analysis.

There is no phased promotion of online learning in Slovenia as can be seen from the image on the left. The main user activity starts on February 22 which is also the date of the first webinar in Slovenia and lasts until March 20th when the last time webinar and online learning were closed. The operations during the rest of the time should be the operations from users registered in advance and the other operations after end.

Luxembourg and Ireland

We put the result of Descriptive Card Mining for Luxembourg and Ireland together because we only collect a few of users' data from these two countries.

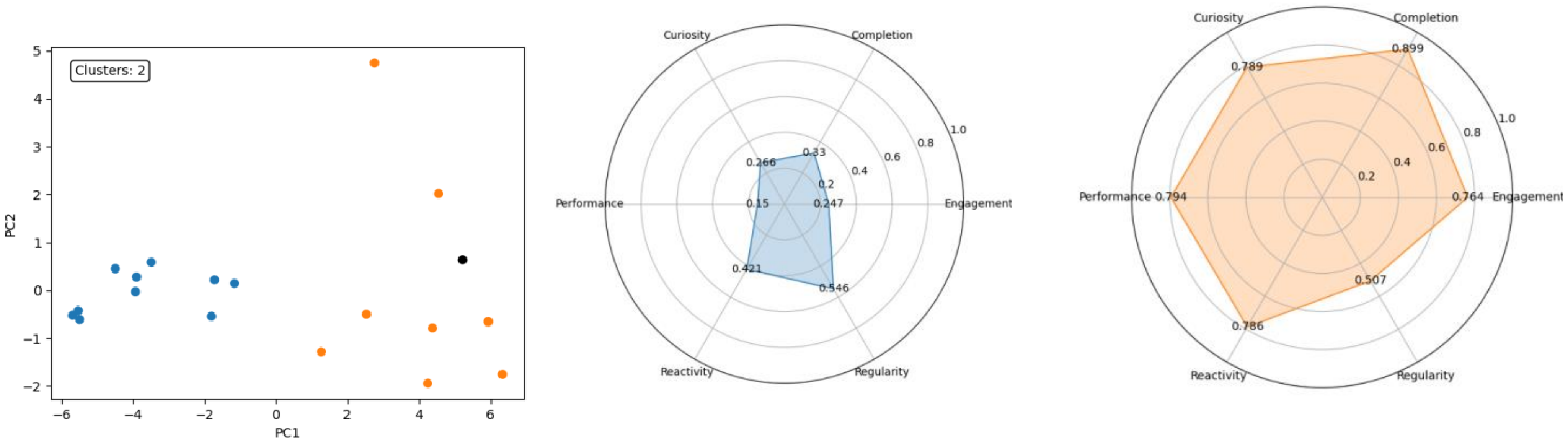


Figure Lux-1: Descriptive Card of Luxembourg.

The left image shows the clustering result for users after visualization, and the right image shows the values of numerical indicators for the corresponding of the clusters in the left image.

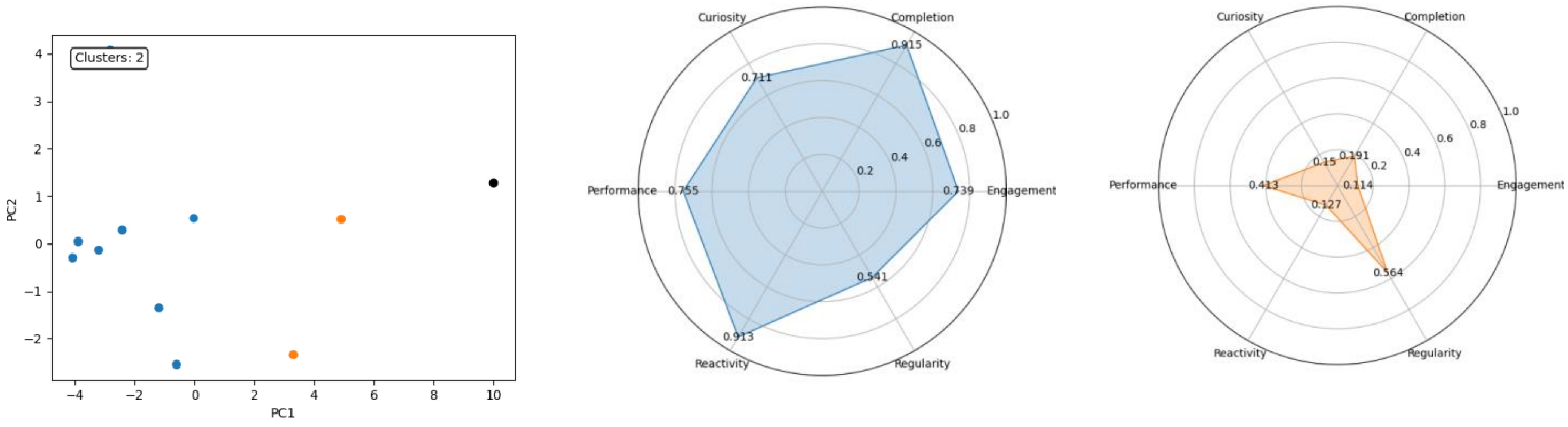


Figure Ire-1: Descriptive Card of Ireland

The left image shows the clustering result for users after visualization, and the right image shows the values of numerical indicators for the corresponding of the clusters in the left image.

As shown in Lux-1 and Ire-1, there are **only 19 users for Luxembourg and 11 users for Ireland**. As can be seen in the right-hand panel of Lux-1, Luxembourg is the only country where the number of user groups with lower indicators is greater than the number of user groups with higher indicators, but the difference is actually only 10 users and 8 users. The result for Ireland is that there are 8 user groups with high indicators and 2 user groups with low indicators. If the three leftmost data points in the left graph of Lux-1 were removed, the results for Luxembourg would be similar to other countries. If the threshold for outlier detection is changed, the result of the analysis for Ireland could be that there is only one user group with 3 outliers. It can therefore be seen that when the number of users used for analysis is too small, even just one or two users whose behaviour is more deviant from the user group can have a huge impact on the overall results of the analysis. It is worth noting that Luxembourg's results are closer to France's, both featuring a small difference in the number of the two user groups, and the indicator with the largest difference is "Performance", which may indicate that users in both countries behave more similarly when receiving training in both countries. Meanwhile, Ireland's data is more similar to Italy and Slovenia, both featuring a large difference in the number of user groups and the indicators with the largest difference are “Completion" and "Reactivity", which also means that the training situation in the three countries may be similar.

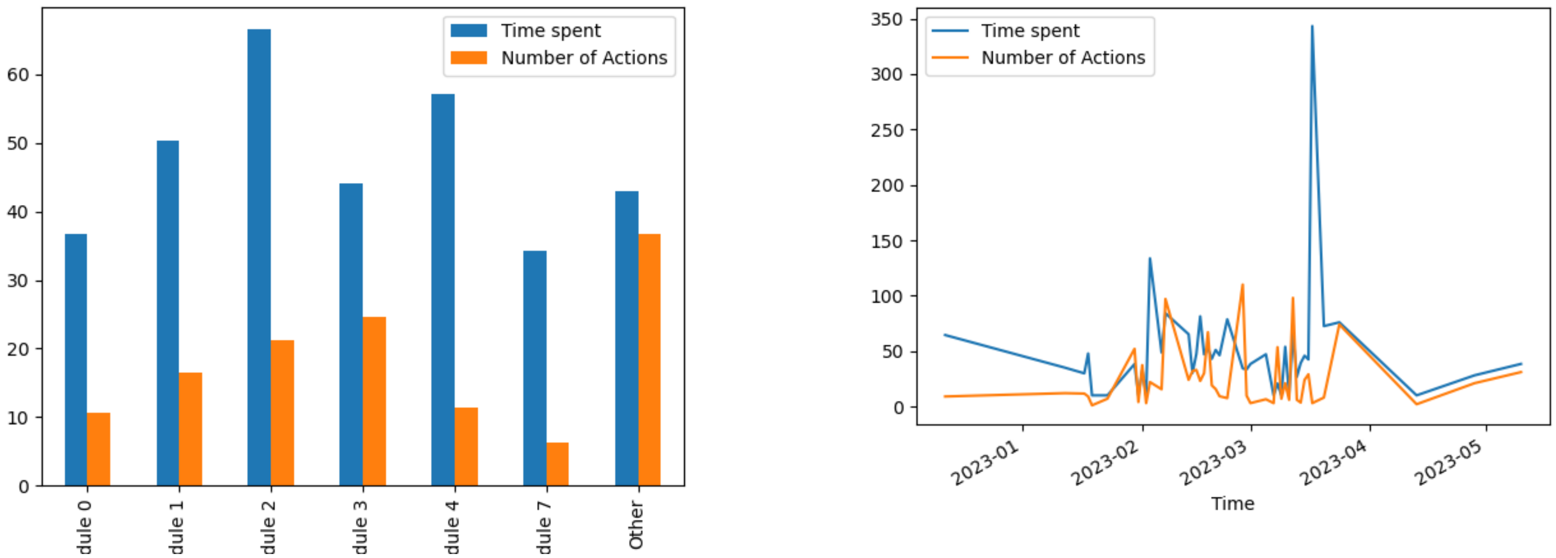
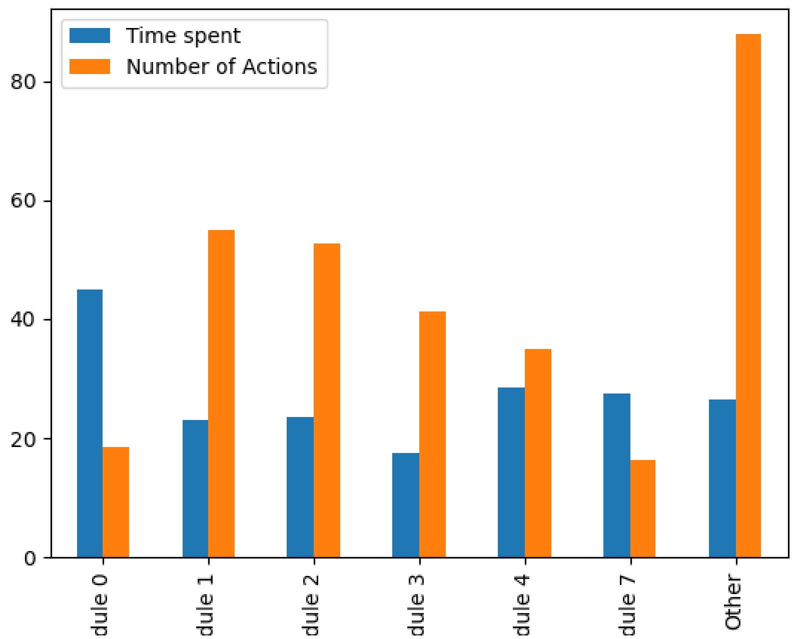


Figure Lux-2: non-numeric indicators for Luxembourg.

The left image shows the distribution of user attention to each module; the right image shows the distribution of user attention over time.



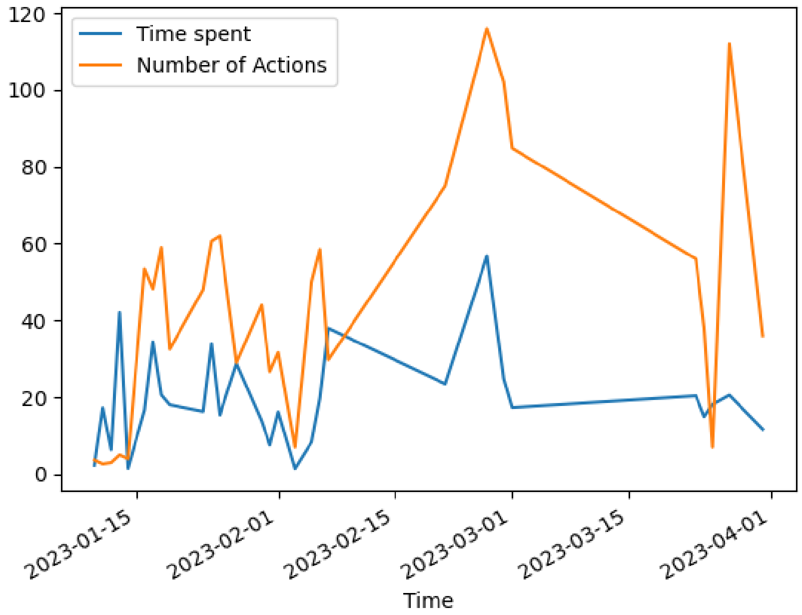


Figure Ire-2: non-numeric indicators for Ireland: the left image shows the distribution of user attention to each module; the right image shows the distribution of user attention over time.

As mentioned before, because the number of users is too small, it is difficult to determine whether the distribution of attention on different modules is affected by this factor, but it is worth noting that module 2 received relatively more attention in these two countries.

In the right image of Figure Lux-2, it could see that the attention distribution curve from January 27 to March 14 is relatively stable, except for the last peak, which should be due to frequent operations caused by submitting results and questionnaires at the end. There is only a small amount of information from early registration and additional operations outside this time.

Ireland divided online courses into Module 1 from January 9th to January 19th, Module 2 and 3 from January 19th to February 7th, and Module 4 from February 7th to March 1st. In the right image of Figure Ire-2, it could see that the **user's operations and time spent start to increase from the third cycle**. Combined with the situation in the left image that users spend more attention on modules 1 and 2, **more users choose to pay attention to online courses only after all courses are introduced**.

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4.2. Commonalities and differences in results across countries

After comparing the Descriptive Card Mining results for the five countries in the previous section, we can find several commonalities:

First, it is obvious that the **clustering result for each country contain exactly two clusters**. Being able to separate out two clusters shows that there are indeed clear differences between users in their willingness, enthusiasm, engagement, etc., to participate in online courses based on the indicators we chose. The fact that there are only two clusters and no more indicates that the **selected indicators do not show significant user anisotropy**. It may be necessary to combine user personal information or *Work Package 3 - Evaluation* findings to compare user differences. In fact, when we compare the calculated indicators by principal component analysis (PCA), **it is found that the "Completion" indicator alone contributed 55.1% of the observed difference, followed closely by "Performance" and "Reactivity".**

Secondly, among the two user groups, except for Luxembourg, **the number of user groups with higher values for each indicator is greater than the number of user groups with lower values**. In fact, even in Luxembourg, the difference is only 8 users versus 10 users, which is more affected by the lower total number of users. This proves that in online learning courses, in general, **more users actively participate, are willing to complete, and respond actively.** This can also be seen from the subsequent global Descriptive Card Mining results.

Finally, for the 5 countries, the difference in "Regularity" indicator between the 2 user groups is very low, **and it can be seen that the user's attention distribution though time is highly related to the training path detail for each country**. On the one hand, it can be thought that users are very obedient to courses arranged according to the training path. On the other hand, it can be thought that the selection of the user "Regularity" indicator should be considered in a longer period of learning or should have more details about time to analysis.

Although some differences in the Descriptive Card Mining results of various countries are identified in the previous section, it is worth adding here that from the results analysis, in addition to the differences caused by users, **most of the differences between countries come from the localization of MOOCs in each country and differences brought about by training path arrangements.** From the analysis of attention distribution, it can be seen that it is difficult to find similarities among various countries, because training programs for online courses and other training (webinars, textbooks, face-to-face training, etc.) are quite different.

Part of these differences are due to language differences, personnel arrangements and other factors in each country, so they exist objectively. The other part is due to the failure to consider the needs of learning analysis and the differences in e-learning platforms in various countries in the initial design of AI4T. This part can be avoided and eliminated in future work.

4.3. Results of the globalization analysis

Different from the Descriptive Card Mining of each country in section 4.1, which is based on the processing and clustering of features, in the global analysis, in order to eliminate the differences and deviations between countries, **we process and cluster the values of the numerical indicators that have been calculated before.**

In Figure Glo-0 presents the results of descriptive card mining for global analysis. In the left image, it can be seen the corresponding data points of users from different countries in the final data analysis in different colors. In the picture on the right, the outlier detection results show that among **530 users, 27 users** are difficult to be classified into the same category as other users and are marked as black outlier data points; the clustering results show that the remaining users are clustered.

The classes are divided into two clusters, identified as a cluster containing 376 blue data points and a cluster containing 127 orange data points. It can be seen that the **data points of various countries are basically mixed together, indicating that the differences between countries are not large**. After splitting the data into two clusters, there are users from 5 countries in both clusters.

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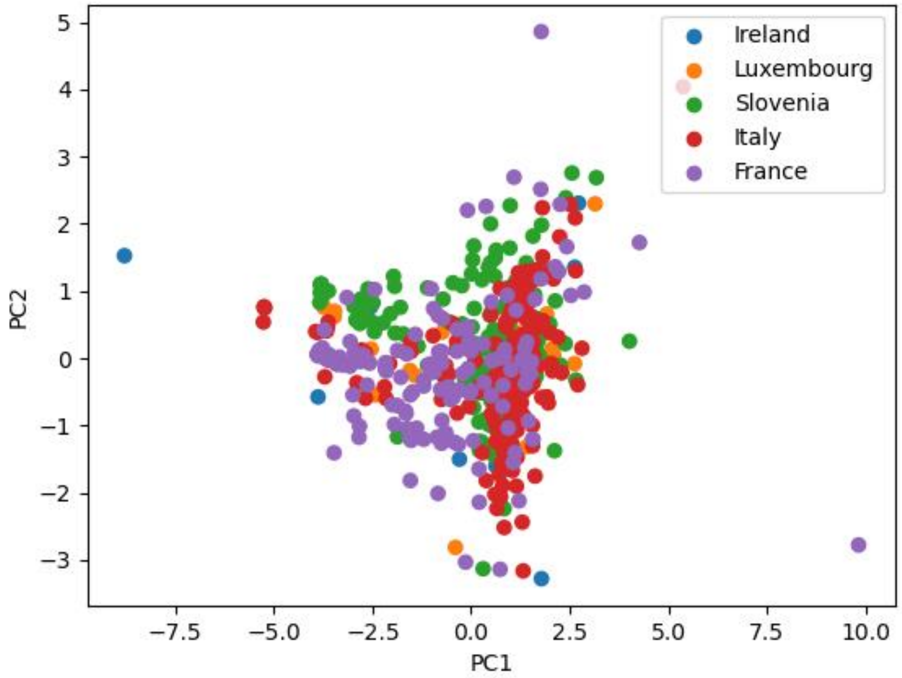

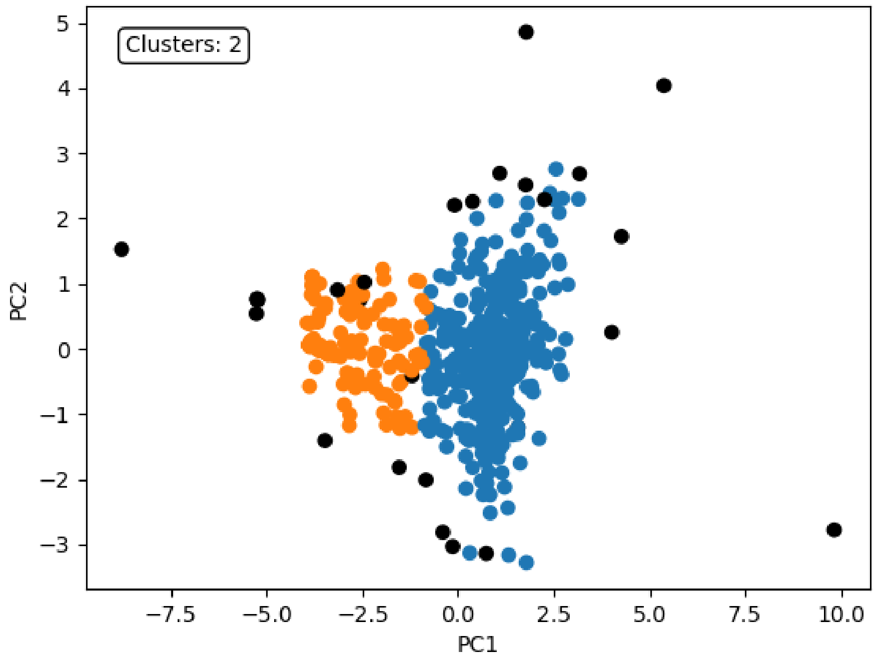

Figure Glo-0: The users after visualization: the left image shows the data points with different colors for users from different country and the right image shows the clustering result.

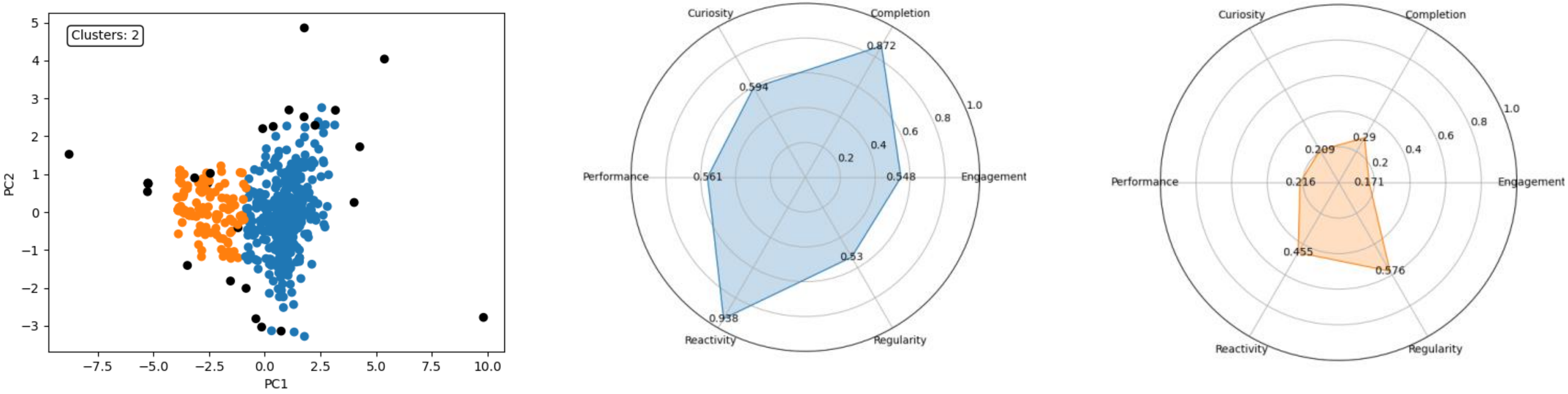

Figure Glo-1: The Descriptive Card of global: the left image shows the clustering result for users after visualization, and the right image shows the values of numerical indicators for the corresponding of the clusters in the left image.

In Figure Glo- 1, above, the left image is identical to the right image in Figure Glo-0, which mainly shows the clustering results.

In Figure Glo-1, the right image shows the numerical indicator values corresponding to the two groups of users, the blue cluster and the orange cluster. **This result is basically similar to the results in Italy, Slovenia and Ireland**. The indicator with the largest difference is "Completion" (distribution of 0.872 and 0.290), which is similar to France, but the difference in "Performance" is not huge. At the same time, the "Regularity" commonality is maintained with minimal differences. As mentioned in the preceding section, note that **two non-numeric indicators, "Attention pattern" and "Time pattern," exhibit a strong correlation with each country's specific training path**. Regrettably, we couldn't identify significant pattern among them by global analysis, and thus, we encountered challenges in devising an effective global analysis method for these two indicators.

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4.4. Analysis and evaluation: What are the implications of these results for education?

In the AI4T project, the *Work Package 3 – Evaluation* leaded by the CNAM-CNESCO from France, are responsible for evaluating the impact of the AI4T professional learning pathway. As it was mentioned in the workflow of AI4T in Section 2.1, the results of this reports are submited to *Work Package 3 - Evaluation* for cross-analyses and regressions.

The WP3 team will receive a table with indicators for each participant on completion, engagement, regularity, reactivity, curiosity and performance in the Mooc. This table will be matched to the results of the questionnaires thanks to a matching between the users ID and the evaluation IDs. *The WP3 will then produce complementary analyses to observe whether learning behaviours on the Mooc modulates the impact of the professional learning pathways on teachers' knowledge, perceptions and use of AI. The descriptive cards will also be discussed in relation to participants' feedbacks on the Mooc.*

More details can be found in the evaluation report of *Work Package 3 – Evaluation* of the project.

5. Conclusion

Within the AI4T project, our efforts have successfully accomplished the following tasks:

- Data collection from diverse platforms in each participating country.
- Implementation of adaptive processing on the gathered data.
- Introduction of indicators as the fundamental elements in data processing and learning analysis.
- Development of the learning analysis theory for Descriptive Card Mining.
- Presentation of Descriptive Card Mining results at both the country-specific and global levels.
- Validation of user performance variations across different countries based on the outcomes of learning analysis.

The research teams expect that these results and the specially the methodology that was used and created will be of use for other projects and research of the field.

As mentioned in the introduction, while online learning has brought a lot of convenience to education nowadays, it has also created many new challenges for learning analytics. Based on the experience gained in the AI4T project and its specificity as a multilateral international partnership, the research team has identified the main challenges and, where possible, developed and implemented risk mitigation strategies for further action.

The difficulties we encountered and the corresponding solutions are mainly as follows:

1, the problem of different logs due to localisation differences in each country: Firstly, we clarified a unified data model, and then searched for corresponding data features according to the data model. Secondly, we adopted the approach of indicators to profile the behaviour of the teachers we focus on at a higher and looser level, avoiding differences in specific features across countries. This process could be used for similar projects with multiple sources of data.

2, we needed a more intuitive way of presenting the data: since this report is to be used both for the evaluation of the subsequent work packages and for presenting the results to those who do not have the learning analyses, we chose descriptive cards, which present the numerical indicators as a numerical degree from 0 to 1 and as a picture of a six-maned star, and the non-numerical indicators in the form of histograms and line graphs. This makes the 0 to 1 values easy to use for subsequent evaluation and the pictures easy to understand for those who do not have the relevant knowledge background.

3, we need to summarise the behavioural properties of the teacher groups in the context of ensuring the security of their data: we propose a descriptive card method. Instead of focusing on specific behaviours of particular teachers, this approach abstracts teachers' online learning traces as indicators in the absence of teacher-specific identities and relevant personal information. Through outlier detection and clustering, it also summarises common patterns across groups of teachers rather than specific teachers. It is worth noting that this approach we propose allows replacing the algorithms in the steps according to different project requirements.

The consortium expects that these final conclusions will be of use for others that can take them as mirrors of “lessons learned. In addition to the issues we have addressed above, here are a few more points that we can prepare from the early stages of the project or address in the future:

First of all, the diverse utilization of MOOC Resources was a major obstacle. Despite offering suggestions, the usage of MOOC resources varied among different countries, leading to discrepancies in the content and formats of collected data. This presented significant hurdles in ensuring data collection integrity and processing uniformity. Secondly, related to the first challenge, we identified non-uniform data availability: the availability of data was uneven across countries, with substantial variations in the number of users. This posed difficulties in ensuring the adaptability and stability of algorithms. Finally, due to variations in training paths across countries, attempts to conduct a global analysis of nonlinear indicators proved unsuccessful. In this sense, a global analysis of Nonlinear Indicators couldn’t be done.

To address these challenges, the leading team (LORIA) proposed the following solutions for future actions:

The first thing to consider would be to assure the standardization of MOOC Resources. The LORIA and the INRIA who were leading the analysis of traces and the creation of the MOOC for the consortium, respectively, have proposed standardized metadata for MOOC resources, which online platforms must adhere to during publication and localization in the future. This will help ensure uniformity in data collection and processing.

If the first point is taken, the second thing to consider would be to uniform the data collection methods. For further projects, it's essential to adopt the same plug-ins and collection methods for resources of the same metadata type to achieve consistency in subsequent data collection efforts. The leading team aims to improve the efficacy of the learning analytic system and address the challenges encountered in the AI4T project.

For further consideration on the methodology created and implemented by the LORIA, the team recommend finding algorithms that remove the bias caused by differences in the number of people in each country. In data mining, the bias introduced by different orders of magnitude of categories is known as imbalance, and there are some algorithms proposed today for imbalanced datasets that can be tried in future work after we get more feedback information for the result. Moreover, researchers could try to improve the quality of the proposed indicators. In the subsequent works, the supervised information coming from the impact study (Work package 3 - Evaluation team) is an important metric to improve the learning analysis algorithm. The assessment of the quality of the AI4T proposed indicators and the correctness of the conclusions of the analyses based on the feedback will help the researchers to improve the definition of the indicators.

6. References

Romero C, Ventura S. Educational data mining and learning analytics: An updated survey[J]. Wiley interdisciplinary reviews: Data mining and knowledge discovery, 2020, 10(3): e1355.

Clow D. An overview of learning analytics[J]. Teaching in Higher Education, 2013, 18(6): 683-695.

Chen L, Chen P, Lin Z. Artificial intelligence in education: A review[J]. Ieee Access, 2020, 8: 75264-75278.

Treuillier, Celina, and Anne Boyer. "Identification of class-representative learner personas." LA4SLE 2021-Learning Analytics for Smart Learning Environments. Vol. 3024. 2021.

Hussain M, Zhu W, Zhang W, Abidi SMR. Student Engagement Predictions in an e-Learning System and Their Impact on Student Course Assessment Scores. Computational Intelligence and Neuroscience. 2018;2018:e6347186.

Arnold KE, Pistilli MD. Course signals at Purdue: using learning analytics to increase student success. In: Proceedings of the 2nd International Conference on Learning Analytics and Knowledge - LAK ’12 [Internet]. Vancouver, British Columbia, Canada: ACM Press; 2012

Boroujeni MS, Sharma K, Kidziński Ł, Lucignano L, Dillenbourg P. How to Quantify Student’s Regularity? In: Verbert K, Sharples M, Klobučar T, editors. Adaptive and Adaptable Learning. Cham: Springer International Publishing; 2016. p. 277–91. (Lecture Notes in Computer Science).