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D2.4 Updated shallow analytics and visualization strategies

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Abstract

This deliverable describes the final shallow analytics and visualization strategies developed for the ENVISAGE project and their implementation. Building from an overview of the state of the art in general Analytics and Game Analytics, it moves on to identify the final requirements and goals for learning analytics and their visualization. We describe the steps followed towards determining shallow and visual analytics under the Envisage project. We also present a general framework for determining which metrics and which visuals should be used in conjunction with a virtual lab or educational game. The framework is then directly applied on the wind energy and the chemistry lab of the project as the final demonstrators of shallow and visual analytics in those labs.

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Executive Summary

This deliverable describes the final visualization strategies developed for the ENVISAGE project and their implementation. Building from an overview of the state of the art in general Analytics and Game Analytics, it moves on to identify the final requirements and goals for learning analytics visualization, building from previous deliverables in the project. A number of visualization strategies are presented and their technical implementation is described.

Abbreviations and Acronyms

CSS	Cascading Style Sheets
DLA	Deep Learning Analytics
HTML	HyperText Markup Language
JS	JavaScript
LA	Learning Analytics
SLA	Shallow Learning Analytics

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1 Introduction

This deliverable outlines strategies for aggregating data of learners in a shallow manner and visualizing those learners' performance in digital learning environments. Within the ENVISAGE project, digital learning environment refer to virtual labs. The ENVISAGE project, in particular, has identified two main virtual labs within which shallow and visual analytics are directly applied: the *wind energy lab* and the variants of the *chemistry lab*. This deliverable provides information about the final implementation of the shallow analysis and the visual exploration of the collected data that aim to provide useful insights into the learners' profiles, actions and performance.

Please note that the type of this deliverable is *Demonstrator* (or Prototype). In other words, it offers high level information about a software solution (for the analysis and visualization of learning analytics) and does not report details on the underlying theory or implementation of the software. Such details can be found in corresponding reports about shallow and visual analytics preceding this deliverable: D1.1 [14], D1.2 [11], D2.1 [9], D2.2 [12] and D2.3 [10]. This companion document, instead, provides the context for the delivered software, explaining the implementation and the design choices made during development. Moreover, this companion document details the software libraries used and the technical implementation employed.

In the following Section, we briefly go through the current state of the art in game analytics (GA) and their visualization, then, in Section 3 we provide the updated requirements for data analytics and data visualization. We do this to leverage the insight that digital learning environments may be different from digital games in their goals, mechanics, dynamic, and aesthetics. A translation of methods, practices, technology from game analytics into learning analytics should take this into account, rather than import these wholesale with no modification. In Section 4, we draw together the information from Sections 2 and 3 and define the design aims of learning analytics in ENVISAGE and the derived visualization strategies. Section 5 and Section 6 describe, respectively, the specific shallow analytics and visualization strategies that we developed to achieve these goals. Finally, Section 7 outlines the technical architecture and implementation used to bring these visualizations to live, in concert with the other software components of the ENVISAGE project.

2 Game and Learning Analytics: From Shallow Data Processing to Visualization

A core idea for the ENVISAGE project is to leverage existing practices and ideas from GA for commercial digital games. To enable this, this section briefly reviews both shallow analytics and visualization strategies in existing commercial solutions. It covers both some general analytics solutions and some game specific analytics solutions.

2.1 Definitions

Before delving into the details of our literature review, in this section we provide some basic definitions of the core concepts met in this report: data, game and learning analytics

Data analytics can be defined as the process of interpreting data by cleaning, transforming and modeling it, for the purpose of uncovering useful information to support decision-making [17, 4].

Data analytics uses methods from applied statistics, data science and artificial intelligence with the aim to interpret an underlying phenomenon within a given dataset; the dataset is supposedly representative of the phenomenon. Within games, the use of analytics takes the form of **game analytics** which is the use of data from players and their interaction with their games to support game development (e.g. monetization) and game experience [17, 6].

Learning analytics is the use of data analytics for learning purposes; hence, it is analytics focused on the collection and analysis of data accumulated to uncover useful information to support education and learning. To put in simpler words learning analytics aims to enhance teaching and learning capacities by means of data of student performance [7]. Via learning analytics, methods from statistics and artificial intelligence can be used directly to identify low performing learners that might require more attention and guidance. In turn both teachers and students may use visualizations of their data to reflect on the learning process or even modify the structure and content of courses. The overall goal of learning analytics is to enhance the learners' performance, to increase retention within educational activities, to reduce institutional cost, to refine pedagogical strategies, and foster academic performance.

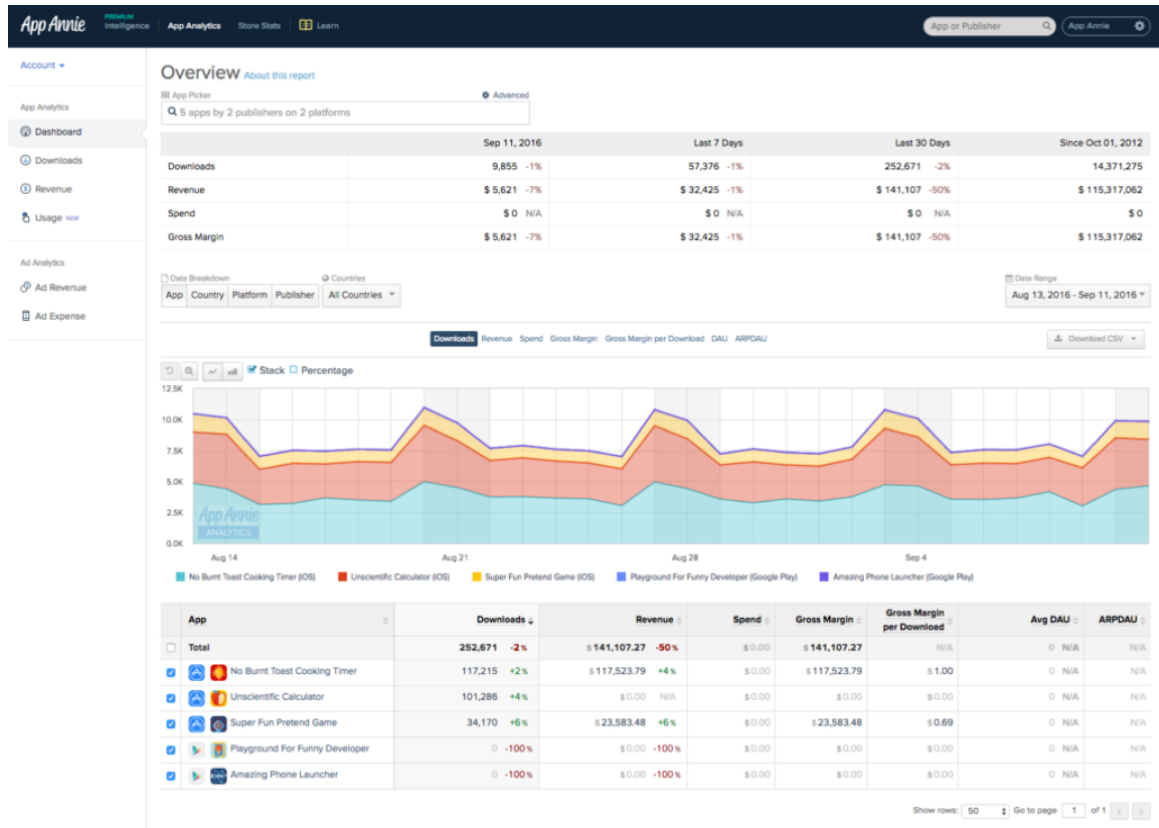
2.2 Shallow and Visual Analytics: From State of the Art to ENVISAGE

To review the current state of the art and practice in visual analytics in D2.3 [10] we identified the most relevant (game) analytics services by conducting a survey of offerings on-line along with a review of the game development professionals' site Gamasutra.com. We also did an informal e-mail and in-person survey within our personal network of professional independent game developers, mobile game developers, AAA game developers, and game researchers. Using this approach, in D2.3 [10] we identified three dominant general-purpose analytics solutions and two analytics solutions commonly used within game development. In the sections below we describe and draw some general conclusions from these visualization solutions. We do not describe these solutions exhaustively, as those are already detailed in D2.3. We however present the most important take-away from each service, focusing on visualization strategies.

2.2.1 General-Purpose Analytics

The *App Annie* [1] is a general analytics platform that provides a number services that may be of interest to commercial game developers. App Annie mostly uses bar charts and line graphs to display the collected values. The services provides a number of features for filtering the collected data in terms of geographical regions, user segments/categories, and date ranges. The longitudinal view of the Annie App proved to be very inspirational for the design of the first round of visual analytics (see Fig. 1a). Yet the temporal aspect of learning turned out to be rather complicated for use in classroom and hence it was omitted from the final visual analytics demonstrator.

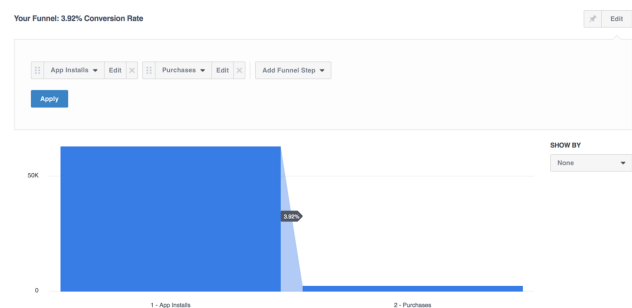
Facebook Analytics is similar to App Annie but puts a particular emphasis on content developed specifically for the Facebook platform. It focuses on tracking the flow of users over time, and provides numerous time-line visualizations and aggregated statistics about users (see Fig. 1b). In terms of visualization, Facebook Analytics mostly uses line graphs, bar charts, pie charts, and tables. The service also supports a Funnel editor and viewing component (and Fig. 1c)) which allows the analyst to see how many users make to the desired end step of a particular process (e.g. purchase) and how



(a) Longitudinal view in App Annie



(b) Cross-sectional view with segments in Facebook Analytics



(c) Conversion view in Facebook Analytics

Figure 1: Two general-purpose analytics solutions considered in our review: App Annie and Facebook Analytics.

many users are lost along the way. This functionality was tested within the framework of learning analytics but was abandoned as overly complicated for the purpose of education and learning.

Google Analytics is another general analytics platform we reviewed (see Fig. 2) which is generally directed at digital content and features many different visualizations and options for customization [10]. Most importantly, it features a *virtual dashboard* that allows for sub-sampling the collected data by defining segments of users and filtering data in terms of time. Once a subsample of users

inspired and utilize snapshots of information shown as bar charts and pie charts which inform educators about student performance. The user flow diagram (see Fig. 2c), is highly useful in the context of digital games [10]; however, the ENVISAGE evaluation studies of visual analytics revealed that the complexity of such a diagram is unnecessarily high for education and thus it was omitted from further investigation and development. The flow diagram is related to the concept of the *travel-path*, as described in D1.1 (3), but the visualization of such a concept seems to be far from understandable for educators.

2.2.2 Analytics for Games

Beyond general-purpose game analytics and according to D2.3 [10] two main analytics services are of interest to game developers: *Game Analytics*¹ and *Unity Analytics*². The first is arguably one of the first analytics services to cater specifically for game developers as it offers a platform tailored for easy integration in the game development process. The platform is focused on showing time-line data with a focus on user acquisition, engagement, and churn, allowing analysts to filter data on a range of variables (see Fig. 3). The service also allows for funnel visualization, data segmentation of users based on custom segmentation condition, error tracking and tracking of game variables over time, typically those pertaining to player state (see Fig. 3). As with general analytics services, *Game Analytics* is driven by event-driven tracking while most of the visualizations are accomplished through line graphs and tables displaying aggregate metrics attached to events.

The second service we consider, *Unity Analytics* provides an offering much akin to that provided by Game Analytics, but targeting solely the Unity game engine. The service is provided as part of the Unity engine (see Fig. 4). The features offered in Unity Analytics roughly match the ones offered in Game Analytics with options for visualizing standard metrics over time, options for segment building, and funnel analysis. Overall, Unity Analytics apply the same visualization strategies as seen above with an emphasis on line and bar charts in combinations with tables to allow for sense-making of the collected data.

2.2.3 Summary

Our core observations from the above mentioned analytics solutions are that a) they are centered on *tracking numbers of users over time* (breaking down users into segments from the data collected or from meta-data available about the users); b) they *track key events* such as the order of visited content and c) they are not oriented toward following individual users closely, but rather focus on displaying analytics in the aggregate (in *groups/segments*). Visualization strategies are centered on using simple and comprehensive *line* and *bar* graphs in conjunction with *tables* to provide analysts with quickly interpretable analytics. We follow all above practices in ENVISAGE and we base shallow and visual analytics on event-driven tracking points, given that is a straight-forward paradigm for collecting data across very different virtual labs and ensuring that the tracking points are placed in ways where they correspond to meaningful events of student performance. However, the above services are not focused on automatically clustering or otherwise segmenting users based on multidimensional models, possibly because different domains require different clustering methods and

¹<https://gameanalytics.com/>

²<https://unity3d.com/solutions/analytics>

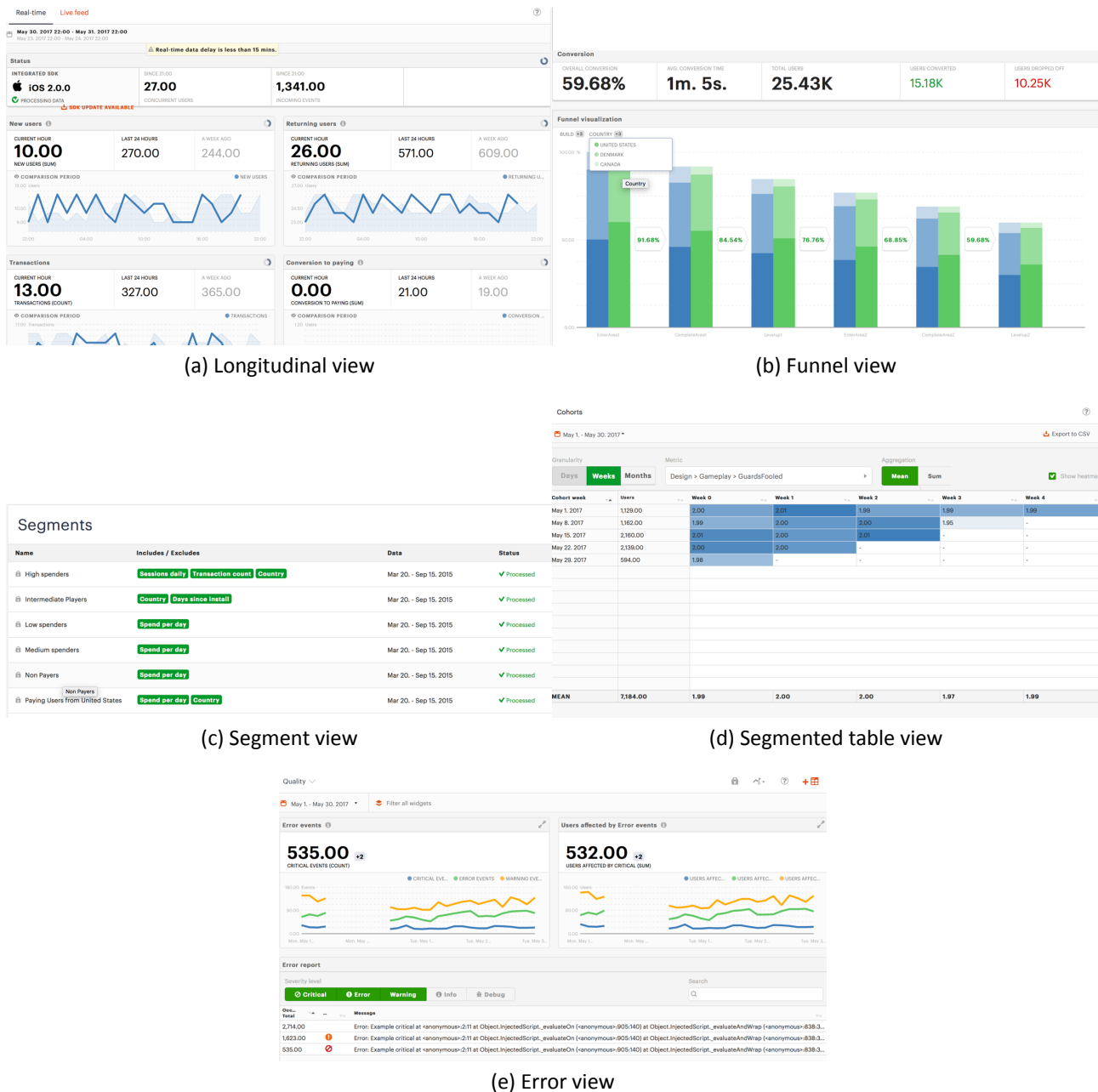


Figure 3: Game Analytics: a core analytics solution that inspired the design of the ENVISAGE shallow and visual analytics functionalities.

different tuning of these methods. In ENVISAGE, instead, we opt for the use of automatic clustering and supervised learning approaches for categorizing students and predicting their performance (see WP3).

This section presented a brief overview of approaches in on-line analytics and game analytics considered in the framework of ENVISAGE, both in terms of general philosophy and visualization strategies. In the following section, we built on the needs for learning analytics determined in the previous deliverables of the ENVISAGE project and we identify the aspects of game analytics technologies—

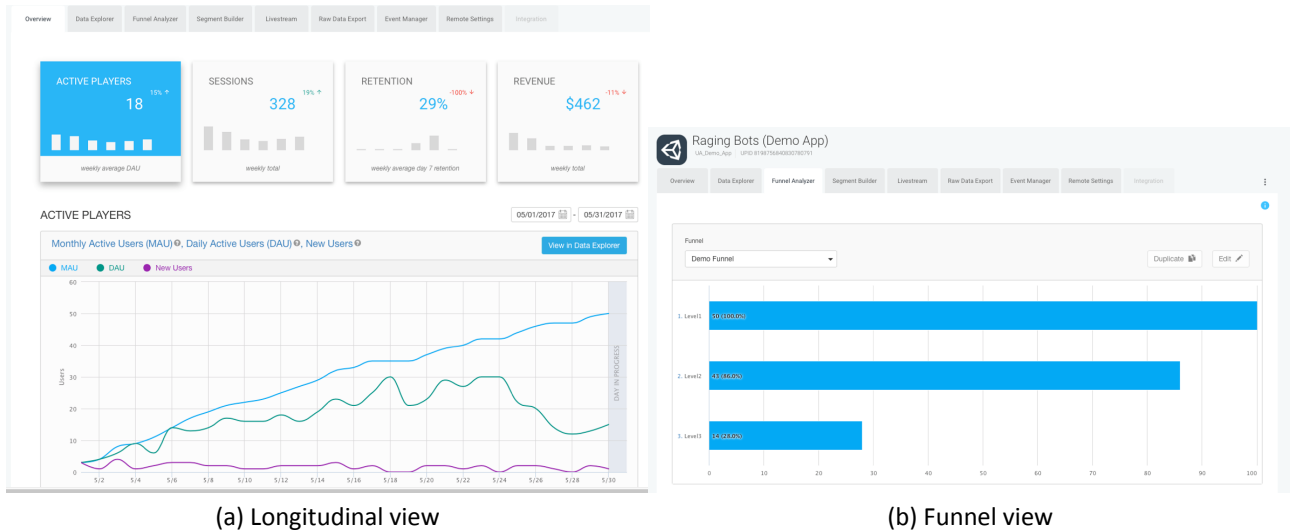


Figure 4: Unity Analytics: a core analytics solution that inspired the design of the ENVISAGE shallow and visual analytics functionalities.

used for shallow data analytics and visual analytics—that may be carried over to learning analytics.

3 Updated Requirements for Data Analysis and Visualization

To finalize the shallow data analysis and visualization principles that can be transferred from game analytics to learning analytics we built on the data analysis and visualization needs that have already been identified and tested within ENVISAGE. We thus build upon findings within shallow analytics and visual analytics in ENVISAGE and derive the final requirements for the analysis and visualization strategies for the project. In particular, we are based primarily on deliverables D1.1 [14], D1.2 [11], D2.1 [9], D2.2 [12] and D2.3 [10]. Collectively these deliverables provide us with an overall understanding on the interests of teachers using and building virtual labs for teaching, the types of data analysis processes that would serve these interests well, and the analytical treatments and supporting architecture necessary to serve these interests.

3.1 Learning requirements

Deliverables D1.2 [11] and D2.2 [12] identify a fundamental need for visualizations allowing teachers to visualize learning behavior and indicators as a) individuals or in groups, allow them to b) contrast individuals to one another, groups to one another, or individuals to groups, and c) allow them to make these comparisons either cross-sectional or longitudinally. Deliverable D5.2 evaluated these questions with regards to the possible visual analytics identified early in the project (D2.3 [10]).

3.1.1 Resolution: Individual-level vs. Group-level

Our goal in ENVISAGE was to allow for a flexible visualization in both groups or at the individual level; doing so requires the easy selection of subsamples of data. The final visualization solutions developed

in ENVISAGE support the easy definition of these criteria. Strategies for accomplishing this have been transferred from the filtering and segmentation methods identified in existing (game) analytics solutions. The final ENVISAGE service with regards to the resolution of data analysis aggregates data on the group level but analytics can be visualized both on the individual and on the group level.

At the individual-level shallow metrics are collected from interactions performed by the individual student in an event-based manner. Student-level metrics can be aggregated into group level metrics which are collected across all interactions from a number of individuals interacting with the same virtual lab; either in the same virtual space or in the multiple instances of the same virtual space.

3.1.2 Contrast: Individuals vs. Groups

To contrast different groups to one another filtering and segmentation is used to create multiple instances of the same visualization, but with different data being displayed. This allows teachers to compare e.g. one student to the rest of the class, students to one another, or two classes to each other.

3.1.3 Time: Cross-sectional vs. Longitudinal

Educators are, in principle, interested in comparing individuals or classes in singular sessions, or track individuals or groups over longer periods of time. In practice however our findings from WP5 reveal that virtual labs are only played for a limited number of times by each individual student during a semester or even a scholastic year. Thus ENVISAGE prioritized for shallow analytics and visualizations appropriate for cross-sectional analysis. Cross-sectional metrics, are collected only once, but across several individuals. While these do not allow for tracking development over time, they allow for comparing between individuals or groups of individuals within a sample. Tracking occurs based on key events triggered by actions of a user in a virtual learning environment.

3.2 Metrics

In this section we expand on the metrics of interest introduced in D1.2 [11] and further discussed in D2.2 [12] and D2.3 [10] with regards to shallow and visual analytics, respectively. In this report we present the final operationalized shallow analytics and visualization strategies based on these metrics. It is worth noting that we consider each metric from the perspective of Stevens's *Theory of Scales of Measurement*[15].

3.2.1 Time-on-task

Time-on-task refers to the time an individual spends engaging with a particular task in the virtual lab. The task itself is defined externally by the designer of the virtual lab, by indicating what triggers the start of a task and what completes a task. Typically, a task starts either in response to a user interaction or in response to a change in the state of the virtual lab. By the same logic, the task ends either as a consequence of a user action or as a consequence of a state change in the virtual lab, driven by the simulation itself. In ENVISAGE virtual labs, the time-on-task, is calculated as the time difference between the defined end time and the defined start time of the task.

The time-on-task is fundamentally a quantitative measure with a meaningful zero point and as such qualifies as being measured on a ratio scale. Visualizing this metric is easily accomplished by *line* graphs or *bar* charts that are scaled linearly to represent the relevant value for the sub-sample in question. Time-on-task may also be range-normalized according to the length of the whole section in which the task was engaged with, presenting a relative measure. Both of these approaches are relevant to educators using ENVISAGE services, depending on whether they are interested in understanding absolutely how much time students spend on particular tasks, or whether they are more interested in understanding how students spend the time that is available to them, relatively, between the tasks. The final ENVISAGE analytics implementation supports both these modes of visualizing this metric.

3.2.2 Time-to-completion

Time-to-completion is also a ratio scale metric, similar to time-on-task; the main difference being the emphasis on measuring the overall time spend from the start of the whole sequence of tasks until the completion of the last task, the learning activity consists of. Time-to-completion is thus a composite of time in a sequence of task. Time-to-completion is also calculated as the difference between the defined end-time end and the defined start-time but will consist of multiple tasks. The resulting metric cannot be normalized for an individual session, but can be range-normalized across all the time taken across multiple sessions to provide a relative visualization. The final analytics implementation presented in this document supports both the analysis and the visualization of this metric for all ENVISAGE virtual labs.

3.2.3 Mastery index

Mastery index describes how well a student is capable of conforming to some objective measure internal to the learning environment in question. For the Wind Energy Lab e.g. this could be the percent of the time where the student was able to keep the simulation in a correctly powered state. Typically, the mastery index will benefit from being normalized to range from 0 to 1 or 0 to 100, since the index describes the space going from complete incompetence to perfect mastery. For the purposes of ENVISAGE we assume that the mastery is measured linearly or can be transformed into a linear form. Given this assumption, this metric is also an interval level measure and hence suited for visualization through line graphs and bar charts that can express how close a student or groups of students are to achieve perfect mastery and can be used to compare students or groups of students.

3.2.4 Levels of proficiency

Levels of Proficiency is a value calculated based on which percentages of a class population reach which performance categories out of “No problem solver”, “Beginner”, “Advanced”, “Reflective”. The metric is an interval level measure which is well suited for visualization through line graphs, bar charts or pie charts in the case of a single class. It corresponds to a segmentation in the analytics solutions presented in Section 2, but an ordered segmentation rather than a completely nominal (categorical) one. The Level of Proficiency can be visualized using a color scale, which can be helpful both when measuring the same class over time or when comparing two classes to one another.

4 Learning Analytics in ENVISAGE: Finalizing Design Aims

Drawing together the findings from the earlier deliverables of ENVISAGE, in this section we set a number of high-level goals for the final design of our learning visualizations and shallow analytics. This allows us to define the final iteration of visualization strategies for the ENVISAGE project. Some of these goals are similar to the goals in commercial game analytics and hence visualization methods can most likely be ported directly from this field. Others are specific to learning analytics and require visualization solutions particular to this field and this project.

4.1 Focus on Cross Sectional visualization

Learning analytics shares the need for both comparing different segments at specific points in time as well as tracking metrics over the course of time. Methods for accomplishing this are well-developed in commercial game analytics, as described in Section 2 and the described approaches of providing aggregate summaries in the form of pie charts, bar charts, and line graphs can be transferred directly from game analytics to learning analytics. However, given the low frequency of in-game interactions with virtual labs of ENVISAGE (and beyond) our solutions supports mainly cross sectional visualizations and shallow analytics. Longitudinal analytics were considered and can be supported but are not of practical use for learning analytics within ENVISAGE.

4.2 Small-Scale Data Analysis and Visualization

While all analytics solutions reviewed in Section 2 aggregate data across large numbers of users, learning analytics within ENVISAGE (see deliverables of WP5) comes with a need for visualizing across a small number of users and possibly only a single session or very few sessions [12]. Based on that finding the ENVISAGE shallow analytics and visualization implementation allows the analyst to receive meaningful visualizations at e.g. the class, sub-class, or group level, or even at the level of an individual user. Given the aims of learning analytics our approach differs from the approaches taken in game analytics in general which typically supposes users in the thousands or millions and as a result focuses predominantly on aggregated data. Datasets arriving from users of virtual labs are also, in practice, much smaller. In turn their processing can be made on small scale and also requires a different set of approaches when it comes to both shallow and deep analytics. For small scale shallow analytics, a small set of features can encapsulate the underlying behavior of a student without the need of either higher resolutions or larger feature vectors. The same principle is directly applicable in deep analytics: simple yet efficient algorithms, such as clustering and linear regression, can deal with the small sample sizes retrieved from virtual labs. Any additional complexity with regards to the method used is unnecessary to the problem of learning from small data sizes.

4.3 Subjective Nature of Learning

As documented in D1.1 [14] and D2.2 [12], it is not given that educators will be able to define objective measures of performance ahead of time, when engaging in Learning Analytics. This could be either due to measures of interest arising from studying the data during Learning Analytics or that the processes of interest take place in an environment that is not trackable i.e. in the mind of the

student or as a social process in the classroom and not in a process that is observable inside the digital learning environment. We can contrast this with regular analytics where the analyst is often interested in objective measures of user behavior. The examples of game analytics we covered in Section 2 focus on metrics such as engagement (how long do users stay within a digital content universe), app launches, and conversions. These metrics are easily defined, measurable and do not concern themselves with learning or developmental changes in the mind of users. Defining an objective for optimization, thus, is typically easier in commercial analytics and game analytics. We suggest that this motivates developing more flexible, customizable, and process-oriented visualizations for learning analytics than standard game analytics. Since the analysts (i.e. teachers designing digital learning experiences, e.g. in the form of virtual labs) may not be able to directly measure the outcome that they are attempting to optimize for, it becomes increasingly important to facilitate data exploration and render salient how students are moving through the digital learning environment. This is mirrored in the emphasis on the travel path metric in D1.1 [14], D1.2 [11], and D2.2[12].

4.4 Segment Discovery via Deep Analytics

For Learning Analytics, the notion of segmenting is useful, much in the same way that it is useful to commercial Game Analytics. Learning Analytics provides several outcome segments that can be calculated objectively and externally, or gained from meta-data about students provided it is possible to identify individual students in the dataset. This could be, for instance, the student's overall performance in the subject that a digital learning environment is designed to teach, represented by e.g. the student's grade in the subject. It could also be the metrics internal to learning analytics, such as e.g. the proficiency level or the mastery index. Nonetheless, teachers or analysts may be interested in mapping these outcome classes to classes that are derived from the collected data, rather from externally defined metrics.

The Deep Analytics module of ENVISAGE (see deliverables of WP3) provides these suggested segmentations through processes of clustering. As we will see in the next section, the visual analytics solution of ENVISAGE covers for the need of segmentation visually and hence support educators and analysts in making sense of the clustering proposed by Deep Analytics. Educators are in turn able to link the provided information to other outcome metrics or objectively defined segmentations. Thus, the final visualization solutions for both shallow and deep learning analytics flexibly support not only the definition and display of segments, but also the discovery (and rejection or confirmation) of potential segmentations derived from patterns in the collected interaction data.

In the following two sections, we describe the final ENVISAGE shallow analytics and visualization strategies that we developed to satisfy the design and learning goals identified here.

5 Updated Shallow Analytics for ENVISAGE Virtual Labs

The detailed data analysis process is described in earlier deliverables of ENVISAGE (WP2). The general process starts by mapping out the learning environment of the virtual lab. This first step provides an overview of which behavioral variables can be tracked, as well as what game states can be represent behavioral traces of players and through which actions. The result of this mapping is the identification of all possible actions which can be perceived as indicators (proxies) of learning. These ad-hoc picked and designed events lead to tracking points that are ultimately used for the extraction of relevant

features based on domain knowledge about a virtual lab. Data are then aggregated based on the picked events, the selected features are compared against particular learning goals and then they are ultimately evaluated for their capacity to capture aspects of a learner's performance during the virtual lab.

Based on the identified learning indicators we also determine the type of *time* dependency the data have with relation to learning (cross-sectional vs. longitudinal) and the type of data *resolution* (individual-level vs. group-level) the tacking should be performed on as described in Section 3.1. Based on the findings of WP2 and WP5 we follow a *cross-sectional* approach and support both *individual-* and *group-level* analytics for all virtual labs considered in ENVISAGE. To support individual-level analytics we perform personal tracking though a login functionality that provides a unique identifier per student.

As we saw earlier the nature of the ENVISAGE virtual labs determines the degree to which particular elements should be tracked and the metrics that can be used. For both labs predictive analytics and profiling is possible if the size of the data set is large enough. However, the nature of learning labs is rather restrictive in that regard and predictions are not possible with telemetry data from one-time use of the lab (i.e. one data point per student).

It is worth noting that a lot of effort was put in the aforementioned process. The design of simple, meaningful and pedagogically relevant features for each independent virtual lab that is considered in ENVISAGE is not an automated process as it needs to involve domain-expert knowledge from educators and lab designers. In the following subsections we detail the features that have been extracted through the shallow analytics approach we adopted. These features are considered, in turn, as input for the implementation of both Visual Analytics (see next section) and the Deep Analytics algorithms of WP3.

5.1 Wind Energy Lab

The final list of features extracted through the shallow analytics process described in D2.2 and considered for both the visual analytics and the deep analytics aspects of ENVISAGE are outlined below. Please note that there are a few variations of shallow analytics between the 2D and the 3D Wind Energy lab. This is due to the different nature and the dissimilar game mechanics featured in the 3D version.

For the 2D Wind Energy Lab:

- Reach Correct Power (Mastery index). This metric measures the time it took the students to reach correct power from a state of being either under or over powered.
- Correctly powered (Time-on-task): The amount of time the student has the wind simulation correctly powered.
- Over powered (Time-on-task): The amount of time a student has the wind simulation over powered.
- Under powered (Time-on-task): The amount of time a student has the wind simulation under powered.

-
- Tasks completed (Boolean check): Has a student interacted with specific elements of the simulation.

For the 3D Wind Energy Lab:

- Score (Mastery index): Based on a combination of features on the simulation itself and a multiple-choice answer post-simulation, the student receives a score between 1 and 10. The formula of the score is provided by educator experts in the Wind Energy Lab. This is an enriched version of the Reach correct power introduced in the 2D lab. The score metric takes into account not only the correct power, but also the profit made from choosing particular turbine setups. Finally it also considers answers to a number of post-simulation questions.
- Correctly powered (Time-on-task): The amount of time the student has the wind simulation correctly powered.
- Over powered (Time-on-task): The amount of time a student has the wind simulation over powered
- Under powered (Time-on-task): The amount of time a student has the wind simulation under powered
- Tasks completed (Boolean check): Has a student interacted with specific elements of the simulation (e.g. repaired a turbine) or achieved some critical goals of the simulation task (e.g. made profit).

5.2 Chemistry Lab

To extract features for the Chemistry Lab we adopted a shallow analytics process similar to that followed with the Wind Energy. The final list of features extracted presented below are considered for both the visual analytics and the deep analytics aspects of ENVISAGE. Similarly to the Wind Energy Lab, there are a few variations of shallow analytics between the 2D and the 3D Chemistry virtual lab. This is due to the different nature and the dissimilar game mechanics featured in the 3D version.

For the 2D chemistry lab:

- Write formula (Boolean check): Did a student write the correct or wrong formula
- Chose bond (Boolean check): Did a student chose the correct or wrong bond
- Write formula (Time-on-Task): The amount of time it took a student to correct the correct formula for each of the molecule

For the 3D chemistry lab:

- Write formula (Boolean check): Did a student write the correct or wrong formula
- Chose homogeneous series (Boolean check): Did a student chose the correct corresponding homogeneous series

-
- Write formula (Time-on-Task): The amount of time it took a student to correct the correct formula for each of the element
 - Build molecule (Time-on-Task): The amount of time it took a student to construct the correct molecule for each of molecule
 - Read the textbook (Boolean check): Has a student interacted with the textbook

6 Updated Visualization Strategies for ENVISAGE Virtual Labs

All visualizations were evaluated through two cycles. During the first cycle, we evaluated the more complex visualizations, such as chord diagrams and force-directed graphs, as introduced in D2.3 [10]. Such visualizations proved to be too challenging for comprehension as educators expressed uncertainty and confusion when trying to read the more complex visualizations in a focus group. As a result of this evaluation study followed in WP5, complicated visualization techniques introduced in D2.3 [10] were omitted for further investigation and implementation from all virtual labs. For the second cycle of evaluation, educators were asked to rank among two or three simple visualization options (which illustrated the same outcome via different visuals) through a questionnaire. The educators had to pick the visualizations they perceived as providing the best overview, most informative etc. The core finding is that educators are in full agreement since they opted for simple, yet comprehensive, visual analytics such as bars, lines and simple segmentations of data. The details of the evaluation process are outside the scope of this deliverable and are described in full detail in D5.2 [13].

In this section we describe the final visualization strategies developed in order to accomplish the goals identified in the previous section. These include basic visualizations such as line and bar charts as well as variants of time-line Visualizations. Finally, extending beyond the use of shallow analytics for visual strategies, this final implementation takes into account visualization strategies for Deep Analytics (e.g. data clustering).

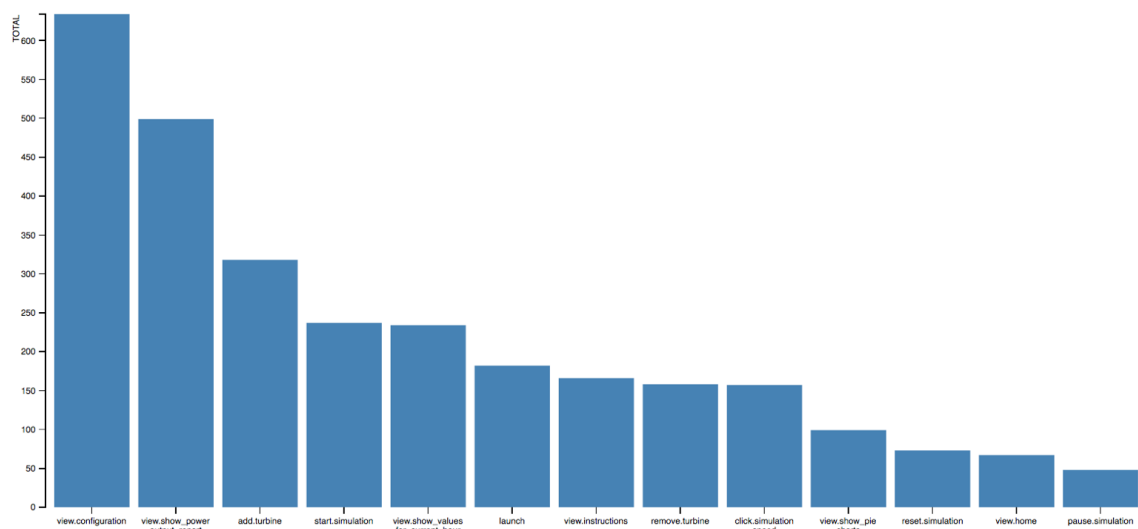


Figure 5: A simple bar chart from the ENVISAGE visualization library.

6.1 ENVISAGE Basic Visualizations: Bar Charts and Line Graphs

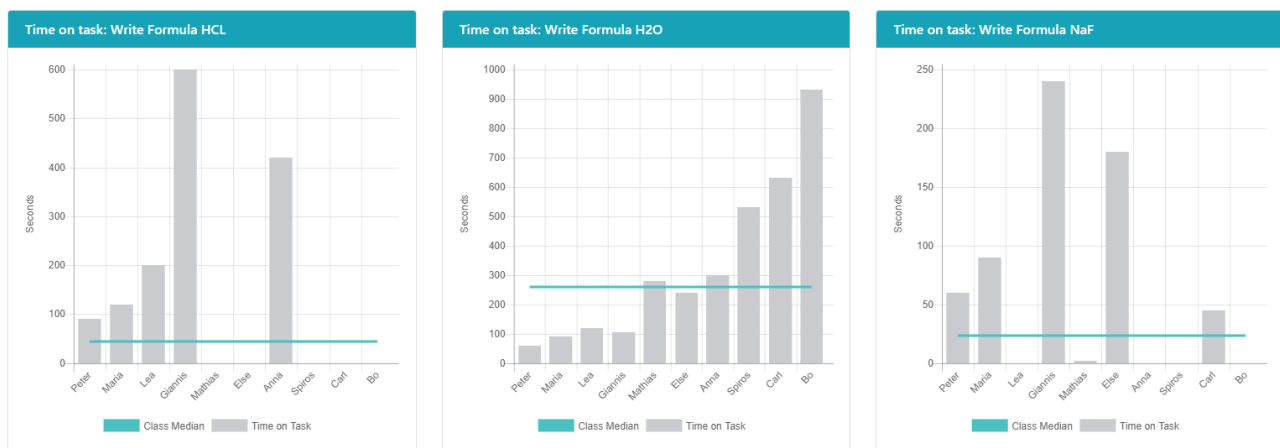


Figure 7: Bar chart and line graph visualizations in the Chemistry Lab. The bar charts of this example illustrate the time it took a student to write various formulas (HCL, H2O and NaF) correctly. The line displays the class median value.

Collected here under one section, we present the basic visualizations developed for Learning Analytics. These are basic aggregated visualizations of shallow analytics features presented above or other relevant metrics that are important to show with regards to their relevance to learning performance. The simple visualizations mirror the implementations of visualizations of aggregate metrics that are common-place in commercial game analytics and are tailored within the ENVISAGE virtual labs. Figures 5, 6 and 7 depict, respectively, a general ENVISAGE bar chart and bar charts as utilized for the Wind Energy and the Chemistry Lab.

Median Time on Task: Reach Correct Power

The median time it took the students to reach correct power from a state of being either under or over powered.



Figure 6: Bar chart and line graph visualizations in Wind Energy Lab. The bar chart illustrates the median time it took a student to reach correct power from a state of being either under or over powered. The line displays the class median value. The different bar colors correspond to the 4 different PISA categories as predicted by the deep analytics module of ENVISAGE (see also section 6.4).

6.2 ENVISAGE Basic Visualizations: Tables

Beyond simple bar chart and line graphs the evaluation studies of WP5 revealed that simple tabular representations of information are very handy for the learning objectives of educators. It appears that data in tables are not only easy to comprehend but also very informative with regards to leaning analytics. Figure 8 shows examples of how tables are used as means for visualizing analytics in the ENVISAGE project.

6.3 ENVISAGE Time-line Visualizations

The time-line visualizations developed for ENVISAGE focus on foregrounding the time spent between different events. The time-line visualization leverages the master index and the travel path metric delivered by Shallow Analytics to display which events each individual user experienced and how much time was spent between each event visit. A simple strategy for adopting this type of visualization

Tasks completed							
✔ Task complete							
	Reached correct power	Added turbine	Turned turbine on/off	Repaired turbine	Changed wind speed	Changed power requirements	Changed simulation speed
Anna	✔	✔			✔	✔	✔
Bo	✔	✔	✔	✔	✔	✔	✔
Bo	✔	✔	✔		✔	✔	✔
Else		✔			✔	✔	✔
Else	✔	✔	✔	✔	✔	✔	✔
Maria	✔	✔	✔	✔	✔	✔	✔
Else	✔	✔	✔		✔	✔	✔
Lea	✔	✔	✔	✔	✔	✔	✔
Giannis	✔	✔			✔	✔	✔
Bo					✔	✔	✔

(a) Wind Energy Lab: In this visualization the table depicts the various tasks completed by each student individually.

Task completion: Write Formula								
✔ Task complete ✖ Attempted but not completed								
	HCL	H2O	NaF	NaCl	KBr	CH4	CaCl2	CF4
Peter	✔	✔	✔	✔	✔	✔	✔	✔
Maria	✔	✔	✔	✔	✔		✖	
Lea	✔	✔	✔	✖	✔			
Giannis	✖	✔	✔	✖	✔		✔	✖
Mathias		✔	✔	✖				
Else		✔	✔	✖			✔	
Anna	✔	✔		✖				
Spiros		✔		✖	✖			
Carl		✔	✖	✖				
Bo		✔		✖				

Task completion: Chose bond								
✔ Correct answer ✖ Wrong answer								
	HCL	H2O	NaF	NaCl	KBr	CH4	CaCl2	CF4
Peter	✔	✔	✔	✔	✖	✔	✖	✔
Maria	✔	✔	✔	✖	✔			
Lea	✖	✖	✔		✖			
Giannis		✔	✖		✔			
Mathias		✔	✔					
Else		✔	✖				✖	
Anna	✖	✔						
Spiros		✔						
Carl		✖						
Bo								

(b) Chemistry Lab: In this visualization, for each student, the table depicts whether the task of *writing a formula* was successfully completed or whether the task was attempted but not completed.

(c) Chemistry Lab. In this visualization the table depicts the correct and wrong answers on the task of *choosing a bond* across all students.

Figure 8: Tabular Visualization examples in ENVISAGE

is the *absolute* time-line approach. This visualization simply labels the time between events with the name of the event at the start of each period and displays information either for each user or averages across groups of users. This allows an analyst compare individuals or groups in terms of how much time they spend in different parts of the digital learning environment, potentially spurring

on insights into reasons for these differences or changes that might move these patterns closer to a desired state.

However, if a high degree of variation is observed in the dataset, e.g. if students spend very different amounts of time overall or on specific tasks, it may become difficult to compare individuals or groups to one another. This limitation turned out to be severe for the comprehension of the absolute real-time visualizations developed in D2.3. In this final implementation of ENVISAGE visual analytics we address this challenge by implementing *relative* time-line Visualizations instead. The relative time-line visualization represents the same metrics as the absolute time-line visualization, but normalizes all total session times to the same visual length, and calculates the time spent between events as a relative fraction of this total amount of time. This means that the activities of students are no longer comparable in terms of the total time taken, but become comparable in terms of where they spend their time, relatively. While this may produce misleading information for datasets with a high degree of variation in terms of the total session length, it may be useful to an educator when the sessions are relatively similar, but not completely. When working with groups, values may again be averaged before this normalization process.

Figure 9 shows an example of this type of visualization for a dataset of the Wind Energy Lab across a number of learners. This visualization additionally may sort the students based on the pattern similarity between their normalized sessions. This may provide an analyst with a quick sorting of the students or groups of students according to their mastery index, which may in turn be combined with segment information to inspire the analyst to various hypotheses about the differences between these segments. An important feature of this type of visualization as implemented in ENVISAGE is that the educator (analyst) may omit (or add) information with regards to the different classes by merely clicking on the corresponding class. For instance one can remove the “under powered” class and solely observe the changes in the remaining two classes (see Fig. 9).

6.4 ENVISAGE Deep Analytics Visualization

The final set of visualization strategies implemented within ENVISAGE are those that illustrate any relevant information provided from the Deep Analytics efforts of the project (WP3). As detailed in the deliverables of WP3 visual analytics are linked to the outcomes of unsupervised learning (clustering) processes which group students in classes of performance. As a result these Deep Analytics visuals inform the educator about the current distribution of class performance and assist her to design more pedagogically relevant labs through the authoring tool.

In Fig. 10 we observe two pie charts that communicate visually the information retrieved from Deep Analytics. Each pie chart visualizes the four PISA performance classes of students: <I. No Problem Solver, I. Beginner, II. Advanced, and III. Reflective (see D1.1 and D1.2). This visualization type of student performance in groups is virtual lab-independent as it relies solely on the PISA categorization clusters which are generic across educational tasks. Similarly to the relative time-line bar charts implemented the Deep Analytics pie charts can be modified by the educator so that particular information is on display. For instance the educator may opt to omit certain classes of student performance (e.g., I. Beginner) and only display the remaining classes).

Besides clustering, work in WP3 is also concerned with the computational adaptation of course material. As described in deliverable D3.2 in greater detail, the content adaptation module currently allows to define different learning strategies. These strategies are then assigned at random to stu-

Power Status

The amount of time the students had the wind simulation correctly, under and over powered.

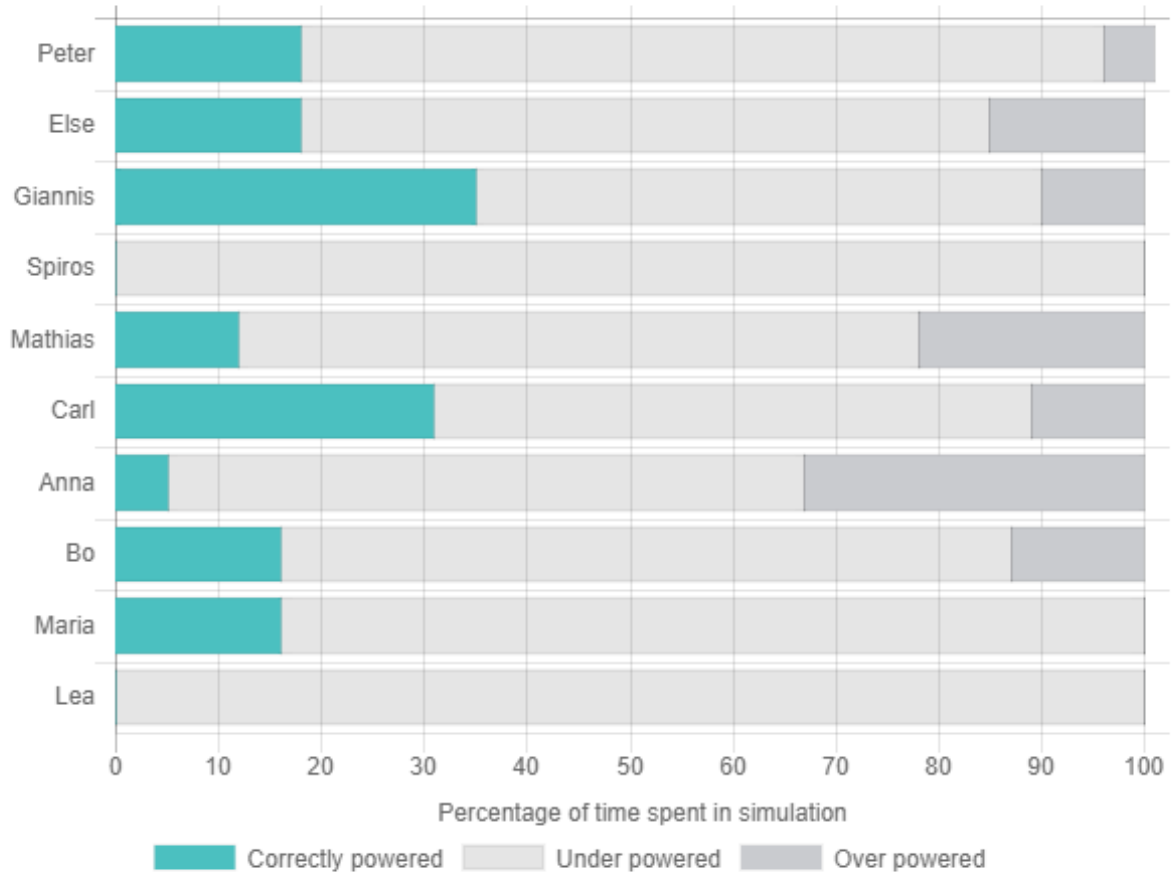


Figure 9: Relative time-line visualization in Wind Energy Lab for a group of students. The graph depicts the relative amount of time the students had the wind simulation running correctly (green color), under (light gray) or over powered (gray).

dents using the virtual labs. Over time, as more students are assigned to the different strategies, the quality of the strategies can be evaluated. Figure 11 shows an example in which different learning strategies are compared over time. As one can see, students who were assigned to strategy s2 performed on average about 16% better than students who were assigned to strategy s1. Eventually, only the most successful strategies will remain but different groups of students may receive varying strategies. The visualization of the strategies' performance is supposed to help the teachers to identify well working strategies.

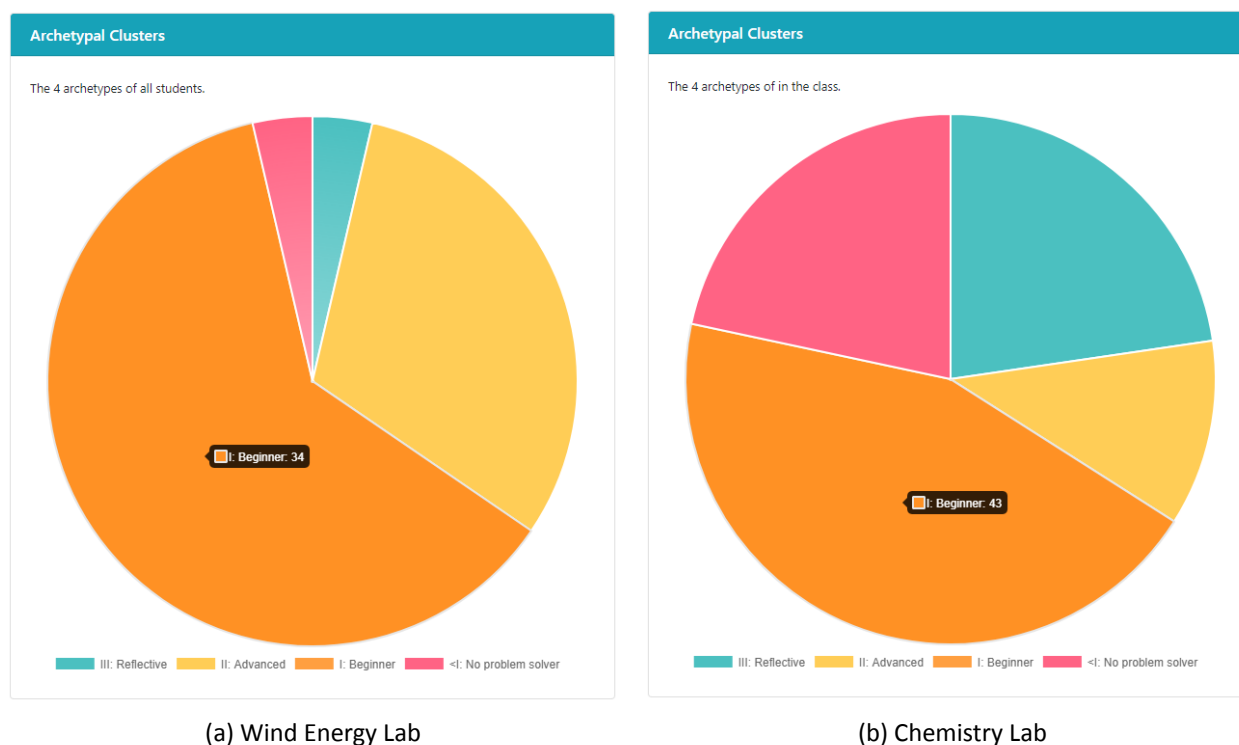


Figure 10: Visualization of Deep Analytics in ENVISAGE. Archetypal Analysis is used on the two virtual labs to derive four clusters of learner performance. The clusters are visualized as colored pie charts indicating the various PISA classification codes. By placing the mouse over the pie chart the educator has access to the amount of students under each PISA category.

7 Technical implementation

In this section we discuss the overall architecture of shallow and visual analytics in connection to the remaining modules of the project. Further it provides the open-source resources for viewing and downloading our solutions

7.1 Overall Architecture

As described in D4.1, the ENVISAGE project employs a distributed software architecture where the various tasks in the project are handled by independent modules that communicate REpresentational State Transfer (REST) [8]. The visualization components developed for ENVISAGE follow these same principles; the visualization software assumes that it may retrieve a dataset, or subsamples of a dataset at URL endpoints provided by the data store solution provided by goedle.io. The received data is then parsed, transformed, and analyzed as necessary, either directly in the visualization implementation or by requesting these transformations and analyses from the implemented Shallow Analytics solution, delivered as part of D2.2 [12]. All JavaScript is executed in the user's browser, as shown in Figure 12 below.

The visualizations implemented for ENVISAGE can be found at the following URL:

<https://github.com/Envisage-H2020/Analytics-Server>

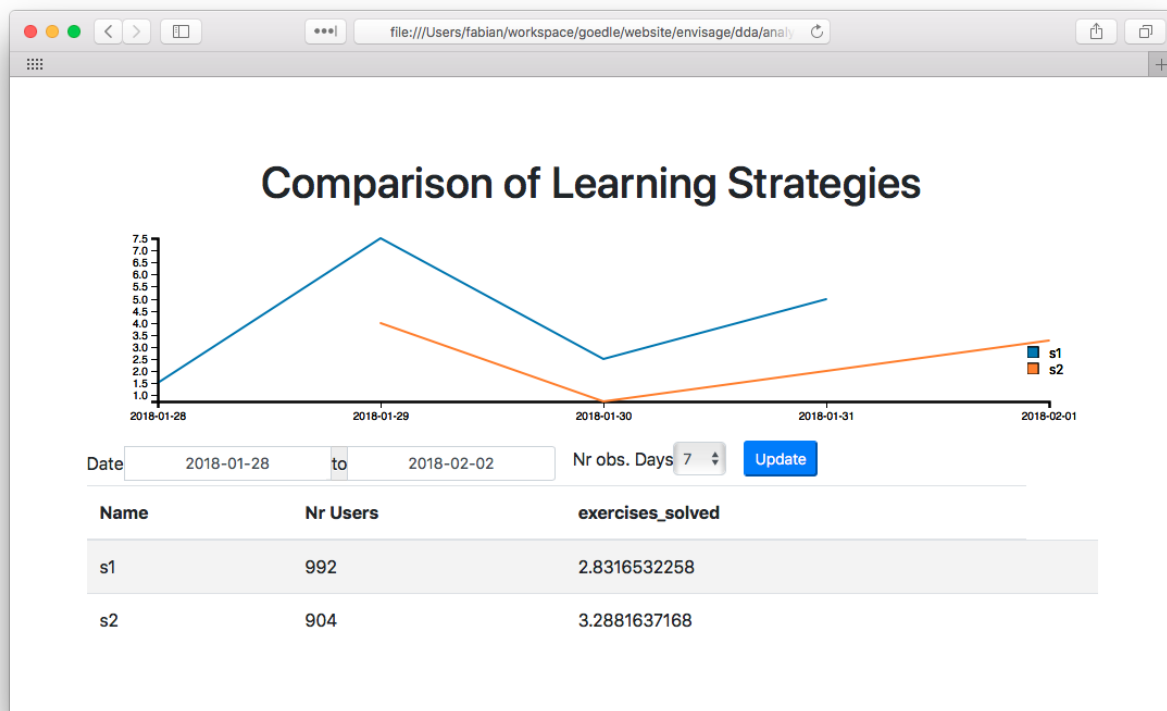


Figure 11: A visual comparison of different learning strategies.

The visualizations implemented for ENVISAGE can be viewed at the following URLs:

Wind Energy Lab (2D):

<http://52.59.219.11/?lab=energy>

Wind Energy Lab (3D):

<http://52.59.219.11/?lab=energy3d>

Chemistry Lab (2D):

<http://52.59.219.11/?lab=chemistry>

Chemistry Lab (3D):

<http://52.59.219.11/?lab=chemistry3d>

8 Conclusion

This deliverable described the background for, the design of, and the implementation of the final shallow analytics and visualization solutions for the ENVISAGE project. The visualization strategies

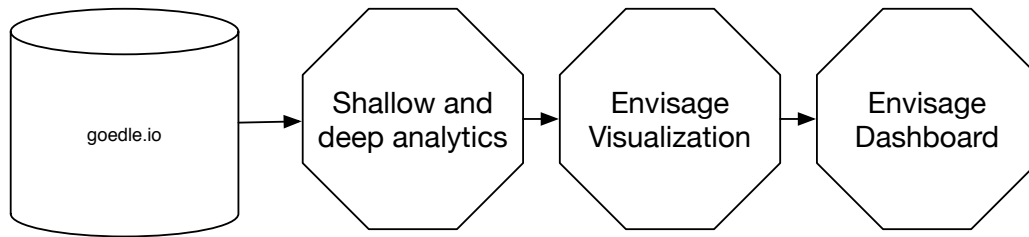


Figure 12: The overall architecture for the visualization part of the ENVISAGE solution. Elements shown in the browser window are calculated and rendered on demand in the user's browser, drawing the goedle.io data server, and the shallow/deep analytics service.

were inspired initially by the state of the art in commercial game analytics and later on informed by the learning goals and pedagogical needs of educators. The final result is a demonstrator for shallow and visual analytics implemented in JavaScript, and the Shallow Analytics library, delivered as part of WP2.

The demonstrator supports many of the identified needs: the ability to conduct cross-sectional analysis, the ability to filter and select on multiple levels, the ability to overview metrics defined in D1.1 and D1.2, the ability to explore the mastery index of students and the ability to observe the behavior of students in PISA performance groups via Deep Analytics.

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