ENVISAGE

ENhance **VI**rtual learning **S**paces using **A**pplied **G**aming in **E**ducation

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D2.2 -User profiling and behavioral modeling based on shallow analytics

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Abstract

This deliverable takes the first steps towards determining how to calculate shallow analytics and presents a framework for determining which metrics should be used with a virtual lab or educational game. The framework is used on the wind energy lab as an example of how metrics could be applied in a specific game context. The metrics time-on-task, time-to-completion and travel-path were identified for the lab and possible calculation of these presented. The deliverable also defines the concept of learning analytics, investigates the stakeholder needs connected to learning analytics services and the ethical implication, which should be reflected upon, when applying them.

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Author list

Organization	Name	Contact Information
AAU	Benedikte Mikkelsen	benedikte@hum.aau.dk
AAU	Line Ebdrup Thomsen	let@hum.aau.dk
UoM	Christoffer Holmgård Pedersen	holmgard@gmail.com
UoM	Georgios N. Yannakakis	georgios.yannakakis@um.edu.mt

Executive Summary

The current deliverable aims to initiate the first identification of appropriate metrics for capturing user profiles and behavioural models. The identification of metrics is based on the analysis of shallow analytics collected from the Go lab Wind Energy Lab. Furthermore, a bottom-up approach is also used, where the learning goals, educational context and design of the lab supports determine how we can track the student behaviour within a simulation or educational game. This deliverable also investigates the needs of different stakeholders in connection with learning analytics and found that educational software developers needs to reflect and manage the diverse interest of different stakeholders simultaneously. Educational software developers need to understand the behavior of students, the context of teaching and develop software solutions that improves these practices and can be sold to management on top. For this purpose, the three metrics Time-on-task, Time-to-completion and Travel-paths was defined and implemented in a prototype to enable profiling on the currently available dataset. A second analysis on a synthetic dataset was also performed to investigate what the implementation of a login system would enable in regards to more precise tracking and profiling. Finally, it is described how the shallow analytics metrics are incorporated into profiles for students and classes.

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1 Introduction

This deliverable presents the initial work on user profiling and behavioral modeling based on shallow analytics. The demonstrator prototype is available on the Envisage project's GitHub repository where the methods related to the calculation of the shallow analytics are collected in the file 3js_projects/js/envisage_shallow.js.[1]

For prototype, we have worked with the data collected from the original version of the GoLab Wind Energy Simulation. In working with this data, we have identified the need for additional tracking points, and data collection, to better support the user profiling and behavioral modeling need to inform the designers of virtual labs. These additional requirements, with the implementation of a login system and tracking that observe the entire game state, will be supported in the authoring tool. Therefore, in addition to the prototype, this deliverable will also propose how shallow analytics can be calculated with the additional tracking data. To demonstrate this, we created synthetic dataset, which exemplifies the type of data excepted to be collected in the future.

Additionally, the deliverable will describe how the calculated metrics will form the basis for the defining profiles for student and classes.

This deliverable will be extended further by D.2.4 where shallow analytics also will be updated and appropriated visualizations will be appointed. Shallow analytics identified at this point will hence have high chances of being updated and changed later in the development process. Changes to current, or addition of new, metrics and calculation of shallow analytics is therefore to be expected as we gain more insights.

First, this deliverable will be presenting a general definition of learning analytics (2. Data Analytics), then move on to describe the possible stakeholders and their needs (3. Stakeholder needs in relation to analytics) and ends with an ethical reflection on the challenges connected with applying learning analytics (4. Ethical concerns related to learning analytics). Afterwards, an outline of the concepts of profiling, behavioral modeling and a hierarchical model of learning analytics will be presented (5. Delineating Analytics, Profiling, and Modeling). Hereafter a conceptual toolkit for implementing learning analytics is presented, along with a hierarchical model of learning analytics, describing how learning goals determines what information should be tracked for learning analytics (6. Learning analytics in practice). Then the implemented prototype developed for this deliverable is presented, showing how profiling can be performed on the currently available dataset, using the metrics identified. Furthermore, a synthetic data set developed for the re-designed version of the 3D energy wind lab is used to propose how profiling and shallow analytics could be calculated more precisely with the implementation of a login system and to fit the new design of the lab better (7. Prototype and Shallow analytics in the Wind Energy Lab). Then it is described how the metrics will be used in building profiles for students and classes (8. From Metrics to Profiles in ENVISAGE). The conclusion of the deliverable will be an investigation of how we can move from shallow user profiling, proposed in this deliverable, to the deep analytics using behavioral modeling and predictions (9. Conclusion).

[1] Link for the prototype: https://github.com/Envisage-H2020/Analytics-Metrics/tree/master/Shallow-Analytics

2 Data Analytics

Data analytics is the process of interpreting data by cleaning, filtering, transforming and modelling it, for the purpose of uncovering useful information to support decision-making (Bihani & Patil, 2014). Data analytics utilizes methods within statistics, computer programming, and operations research to interpret a given dataset. Analytics is used within a variety of industries and research domains to predict, monitor and understand behavior or events.

2.1 General definition of analytics

Within the domain of analytics, in games, the following words are often used: game metrics, game telemetry, and game analytics but with varying definitions. A definition of the terms is therefore provided. Game analytics is the utilization of analytics to support game development and research, with the goal of enabling decision-making on multiple levels of an organization (El-Nasr, Drachen, & Canossa, 2013). Game analytics has become an increasingly essential part in collecting business intelligence and sophisticated tools and methods are available for this purpose.

In recent years, an increasing number of industries have adapted their business models to be more data-driven. Now, companies across the whole game industry have started to collect game telemetry. Telemetry is defined as data obtained over a distance and can be the tracking of a player's actions transmitted to a server (El-Nasr, Drachen, & Canossa, 2013). Game metrics can be the product of raw telemetry, which is transformed into metrics by interpreting the data e.g. “Churn”, “Player retention” and “Daily Active Users”. It is also summarized as the interpretable quantitative measures of attributes of property of objects (El-Nasr, Drachen, & Canossa, 2013).

2.2 Definition of learning analytics

The definition of learning analytics is close to that of data analytics, as it is focused on the collection and analysis of data accumulated to uncover useful information to support decision-making. In particular learning analytics is aiming on assessing the behavior of educational communities (Larusson & White, 2014). A broad definition of learning analytics is the goal of improving teaching and learning by the means of data analysis of student demographic and performance data (Fritz, 2010; Elias, 2011). Statistical techniques and predictive modeling can be used to identify vulnerable learners that need more attention and guidance to decrease the risk of low performance. Teachers and students may use visualizations or taxonomies to reflect on their own learning process or change the structure and content of courses. Regardless of the methods and techniques used to uncover the behavior of educational communities, the ultimate goal is to optimize both students', teachers' and faculty's performance and effectiveness to increase retention and reduce institutional cost, refine pedagogical strategies, and increase academic performance.

3 Stakeholder needs in relation to analytics

Because learning analytics can serve various purposes, it also involves several stakeholders who all have different needs and concerns. The application of learning analytics can e.g. be focused on learners, teachers, parents, researchers, system developers, legislators in education and educational institutions, like administrators and faculty (Chatti, Dyckhoff, Schroeder, & Thüs, 2012). We decided to explore multiple stakeholders, as the interest of a teacher who develops virtual labs will correspond with the needs of both students, teachers and developers. When designing virtual labs, it will e.g. both be in the students, teachers and developers interest to develop labs, which motivates and engages its users with the learning material. Because the end-users of the lab will determine its quality, attempting to facilitate multiple stakeholder needs in the analytics implementation is of essence. Mapping their experience can help the designer validate if the lab had the desired outcome, when applied in a learning context.

3.1 Learners

Learners will undoubtedly be concerned with how virtual lab could help them improve their grades and reach academic goals. The labs might also support the learners to identify in which areas they need to improve, what study activities they need spend more time doing, and help them build personal learning environments.

Parents are also interested in helping their children reach their academic potential and improve their grades. Furthermore, parents will probably be a more prominent stakeholder for children in primary school, or elementary school, as the children might not able to determine themselves, which labs they want to interact with, in the same way as high school and university students are. Within the stakeholder “Learners”, the requirement for a system using a learning analytics dashboards is quite diverse and methods for feedback need to suit the receiver. Visualization is a good example of a method of feedback that would need to be adjusted according to the age and educational level of the learners. Studies found that most students are able to interpret visualizations communicated by a dashboard, to uncover gaps between their desired and actual performance and to change their study strategies accordingly (Park & Jo, 2015; Corrin & Barba, 2015). However, these learners were engaged in higher education and to compare university students’ abilities to interpret visualization with those of learners in primary or elementary school is not appropriate. Corrin and Barba (2015) also found that 17% of students in higher education struggled in interpreting the feedback on a level that would enable altering their learning strategies, in order to fill their gaps in knowledge. The recommendation is therefore to provide students with support resources and establish process to insure students’ abilities in translating the dashboard supported feedback. Visualization can thus be difficult to make sense of for learners on a lower educational level and they might need the feedback to be communicated by a teacher or parent in order to perceive the feedback as meaningful. The design if in-game feedback on performance is therefore a key factor when developing a virtual lab.

3.2 Teachers (not developing labs)

Teachers might be interested in how labs can improve the effectiveness of their teaching practices and support them in personalizing learning to meet individual student needs. Using virtual labs or games during their teaching also enables a move from tutoring to mentoring, where the teacher transfers the control to the student and the focus becomes a more holistic view of the learners, not just their teaching process (Chatti, Dyckhoff, Schroeder, & Thüs, 2012). When the students own their individual learning process, the learning model shifts from an emphasis on knowledge-push, performed by the teachers, to a knowledge-pull from the students. Normally, the teachers "push" knowledge towards the students by deciding how and what the students are being taught. They control the information flow. Whereas in case of "pull" the student initiates and navigates towards the knowledge supported by the learning analytics (Chatti, Dyckhoff, Schroeder, & Thüs, 2012).

3.3 Educational institutions

Educational institutions could be interested in using virtual labs as a tool for supporting students with low performance. Providing the students with new learning environments that could help lower retention and improve student satisfaction would be probably be well received by educational management. "At-risk" students could maybe also be located, using the analytics, and guided to diminish student retention (Campbell, DeBlois, & Oblinger, 2007; ECAR, 2015). Applying labs could also help unburden the teacher who can step into the role of mentor, while the student interacts with the virtual labs accordingly.

3.4 Developers and researchers

For developers of virtual labs, enabling the utilization of learning analytics to inform evolution and re-design, generic guidelines for tracking points and metrics could be helpful. The analytics level of proficiency are dependent on a large body of data to enable predictions and comparisons between individuals, classes and educational institutions.

Developers and researchers have a common objective of implementing features, which translate the data into meaningful information, processed by non-experts in statistics, analytics and data mining. The stakeholders will be interested in information processed and analyzed differently, to fit their needs. Incorrect conclusions might be drawn based on the output of the analytics if the dataset is not big enough, the data is collected based using a different user group than intended etc. Using visualizations is one method of presenting a large amount of information in a more manageable way. Nevertheless, visualizations can be presented in a number of ways and understanding our end-users (e.g. teachers developing virtual labs) is therefore a key factor in deciding on the appropriate visualization. However, there might even be considerable diversity within our end-user segment and providing the users with more than one method of visualizing their data might be beneficial.

4 Ethical concerns related to learning analytics

Learning analytics has evolved from its neighboring research domains, sharing methodologies and theories with e.g. business intelligence, data analytics and learning (Ferguson, 2012). Individual ethical principles and guidelines for each of the domains have been developed but the ethical reflections are commonly similar for themes as user consent, data ownership, privacy, data storage etc. Learning analytics has become increasingly popular in higher education and universities around the world that have seen the huge potential that analytics possess (Johnson, Adams, & Cummins, 2012). Despite the numerous advantages of utilizing learning analytics, a number of ethical issues remains unsolved (Siemens, 2012). Although other authors reflect on ethical issues related to learning analytics, only a few attempts to map ethical concerns connected to learning analytics for higher education and even fewer for the lower educational levels (Slade & Prinsloo, 2013).

The results of ethical reflections will vary depending on the perceptive occupied. For this analysis, a socio-critical perspective is proposed. It focuses on the role of power, the impact of surveillance, the need for transparency and the acknowledgment of the learner's identity as being changeable and context dependent (Slade & Prinsloo, 2013). This perspective allows us to be critically aware of how our diverse contexts and power relationships shape the response to ethical dilemmas in learning analytics. Learning analytics fall into the following broad types of concern:

1. The role of power
2. The location and interpretation of data
3. Informed consent, data ownership and privacy
4. Data management, classification, and storage

4.1 The role of power

The authoring tool will, when it has been developed, be used within organizations of education as the context for its developed labs. Among the stakeholders, presented earlier in this chapter, a set of power relations exists, as in any organization. If perceived through Foucault's Panopticon, the structural design of the organization consents the surveillance of activity by a central authority (Foucault, 1977). In panopticism the head of the organization "school" (e.g. management and faculty) would watch the students and the teachers. In our case, it would be the developers. It would be "the few watching the many". Currently in learning analytics, this is the case, as data are often only available for a limited group, who use the information for decision-making. However, today's access to the internet have enabled synopticon functions. Knox (2010) talks about rhizomatic surveillance, as an active and multidimensional flow of the act surveillance, which by Mathiesen (1997) is described as "the many watching the few". Through social media, we are able to watch others and share personal data online in a way, which was not possible before. The commercial utilization of surveillance and the attitude towards sharing personal data appears to becoming increasingly more accepted and using analytics collected through a virtual lab within a school lessons, would not be more invading than using social media. However, learners have been found changing their behavior when they are aware of surveillance (Adams & Van Manen, 2006; Dawson, 2006). However, this should not be an issue in our case since the developers or/and teachers are not able to identify individual student in the dataset.

4.2 Location and interpretation of data

Learning activities today take places in multiple different platforms and contexts, distributing the data across a variety of sites and services, with different standards for ownership and access to the produced data. Furthermore, some learning activities will be supported by the means of technology and others will not. Creating coherent insights reflecting the students as a whole is therefore challenging and drawing assumptions for the missing or incomplete data, can thus be required to identify correlation between different variables. In our case, the developer will receive analytics from tracking which he or she did not witness himself or herself. However, these assumptions are interpretation of the analyst who subconsciously may have biased the data. Modelling of behavior entails assumptions. As an example, this means that the developer will not know the context in which the tracking was performed e.g. if there were more than one student using the computer for collaboratively solve the tasks. The developer will therefore probably assume that the lab is used for the intended practice and analyze the data accordingly. Consequently, these assumptions will contribute to determining how the lab is re-designed is carried out. Even though we are not able to track all the data relevant for the individual students, the data that we are able to collect also necessitate extensive filtering to transform the raw telemetry into valuable and meaningful learning relevant information. The implemented metrics will support the developer when analyzing the learning analytics, however a self-awareness of the role as an analyst and the responsibilities is requires is advised.

4.3 Informed consent, data ownership and privacy

Informed consent is an established practice within research but the use of student related data in an organizational context has no such practice (Slade & Prinsloo, 2013). In some circumstances, legislation is already protecting the user. Data protection legislation is e.g. providing the user with the choice of accepting a cookie on a website and hereby giving the website permission to store his/her actions. In this case, the user is provided with information about how the data are stored, for how long, for what purpose they are used for etc. By accepting a cookie, the user is giving consent to the terms and conditions stated by the website, which within EU border needs to follow the legislations of data protection.

In some extreme cases, informed consent can be omitted altogether, if the benefit to the many exceeds the needs of the individual. However, this is not applicable to learning analytics as there is no reason not to inform the student of what the tracked data will be used for. However, another issue arises for young learners, as they might not possess the ability to understand the full extent for their acceptance. In a research project, the researchers would need to obtain the assessment of the child participant (if under the age of 18) and a parental permission. However, this is not as transparent when children play or use commercial products online. In these cases, the player is often only identified by the IP address of access device and thus still anonymous. Furthermore, they accept terms when downloading the app, which most user do not spend time reading through carefully. Furthermore, the value created from using learning analytics can directly benefit the student (enhanced learning) as opposed to the commercial games, where the companies also benefit directly by e.g. increased monetization. The benefit to the many could for learning analytics be categorized as high and the potential for harming the users low.

4.4 Data management, classification, and storage.

Determining ownership over data obtained from the internet can be challenging, due to cross board location of servers, databanks, datasets, and end-users. International legislation exists but only covers parts of the world, e.g. the EU Data Protection Reform (European Commission, 2012). As a result, ownership over data can become ambiguous. The institution or company, who facilitates learning analytics related software, should provide guidelines and guarantees of safe preservation and storage of their data and which are in line with both national and international legislation. Data should also be encrypted to ensure users' anonymity and avoid misuse of the data. Learning analytics service providers or institutions also need to be aware that users are, in some countries, able to apply for alteration or permanent removal of personal data, which might be inaccurate if outdated (Slade & Prinsloo, 2013).

Because of the imbalance of power in the relationship between young students and the educational institution, a responsibility should be assumed by the institution to protect against unauthorized access to student data. A data-classification structure, sorting the system data into categories that determine the required level of protection is an essential tool for data-governance. Due to legislation and depending on country, the process might depend on whether the organization is private or public. Petersen (2012, p. 46) suggested a classification scheme to include the categories Public, Non-public and sensitive or Regulatory for public colleges.

4.5 The impact of feedback

Another point to be taken into consideration is the effect of long-term performance when students are being provided with negative assessments on their current performance. McKay (2017) exemplifies this with chemistry placement test used within the American university system. To determine the level a student processes within chemistry, the test is used. Hereby, the test decides if the student would benefit from an entry-level chemistry class or can start organic chemistry straight away without the course. The objective of the course is to provide the lower performing student with a better starting point for learning organic chemistry. However, the improvement in grade, for students who did the entry-level course, is only about 0.2-letter grade. According to McKay (2017), this indicates a great disservice for student who are already among the weakest in class, as singling out this group "the weak" will determine their chances of academic success.

Hattie (2009) also found this tendency in his synthesis of more than 50.000 studies, using statistical measures to compare impact on student achievement. Class size, holidays, feedback and learning strategy's effect size were compared with the students' educational achievement and found that the most powerful impact factor was self-reported grades (effect size 1.44) (Hattie, Visible Learning: A Synthesis of Over 800 Meta-Analyses Relating to Achievement, 2009). Self-reported grades, refer to the students as being the most accurate in predicting their own performance. In a later study, Hattie, Master and Birch (2015) furthermore found that also teachers' estimates of achievement (Effect size 1.62) and collective teacher efficacy (Effect size 1.57) scored high in impact on learning. The relationship between how the students and teachers assess the individual learners' abilities and the acceptance of teachers has huge influence on learning, bears a great responsibility for how the learner actually end up performing.

If the aim of this project is, to determine how the use of learning analytics can support and improve learning outputs, the need for reflecting on and incorporating features that facilitates positive estimates and feedback between teachers and students is necessary. Instead of visually informing the student, of being the lowest performing in class and thus preceding being so.

5 Delineating Analytics, Profiling, and Modeling

This deliverable focuses on shallow analytics as opposed to deep analytics. Therefore, it is useful to explain where we draw the distinction by defining the two concepts.

Shallow analytics refers to presenting data observed about students, for the individual or across individuals. These data will typically be aggregated across observations within the same student or aggregated across multiple students e.g. a school class. The key here is that the information presented is drawn from concretely observed values relevant to one or more students. Shallow analytics is strongly related to user profiling (see below).

Deep analytics, on the other hand, refers to information extrapolated about students from patterns in the observed data. This could e.g. include clustering of students into different categories or predicting values such as inferring future performance given observed historical performance. Deep analytics is strongly related to behavioral modeling (see below).

User profile refers to the collection of personal information about individual users in a given system. User profiling provides a descriptive representation of a user. In learning environments, such as the virtual labs, user profiling can contain descriptive information about learners and teachers e.g. demographic data, performance data, administrative data and the event tracking from the digital learning environment.

Behavioral modeling refers to computational modeling of users based on static data as well as data generated by the user during their interactions with the system. A behavioral model generates new data points and is a dynamic representation of the users, which can predict future interaction.

5.1 A Hierarchical Model of Learning Analytics

A fundamental requirement for enabling learning analytics is to decide what level of analysis will be accomplished. We propose that learning analytics may be subdivided into three levels of increasing complexity, one building upon the other: *descriptive analytics*, *interpretative analytics*, and *model based and predictive analytics*. The first two categories belong mainly to shallow analytics while the third category belongs to deep analytics. In the following subsections, we define each category further.

Descriptive Analytics

Descriptive analytics refers to the application of analytics to the basic raw data as stored in the user profile (see description above). In this case, the task of interpretation is relegated to the expert, e.g. the teacher observing different representations of the data. The observed data are simply reported using various mathematical procedures. An example could be the average time spent with a particular task in a learning environment. Presenting a user with a number or visualization communicating this information does not assign meaning to the information, but provides a starting point for the user to make their interpretations.

Interpretative Analytics

In the case of interpretative analytics, a particular interpretation of the observed data is encoded into the analytic model. Rather than reporting aggregates of simple features, this kind of analytics reports on the attainment of or adherence to particular learning goals. While potentially more informative, this kind of analytics is dependent on the specification high-order concepts that describe how a student or group(s) of students is performing relative to desired learning goals. An example of a specification could be an expert defining that an increasing amount of time spent on a particular task is indicative of increasing attainment of a particular learning goal. An interpretative analytical solution would then automatically evaluate a student or a group of students, based on the time spent on the task and report not the base values, but an interpreted score indicative of how the student(s) had progressed toward attaining the stated learning goals.

Model-Based and Predictive Analytics

Model-based and predictive analytics use previously observed values to build models of individual students or groups of students. These models may then, in turn, be used to predict future lower-level values, future higher-order values, or they may be used to group or otherwise characterize students based on the values observed in the user profile. The key characteristic of this approach is that new values are synthesized based on the actually observed values. An example could be to predict user behavior in a yet un-played educational scenario from actions observed in a previously completed scenario, or it could be the prediction of higher order values, such as future student performance, based on previously observed actions for performance values. It could also include the categorization of students into e.g. high-performing, medium-performing, and low-performing students through clustering on either low-level or high-level values.

6 Learning analytics in practice

In order to provide useful descriptive, interpretative, and predictive learning analytics for a given learning environment, we need to know the learning goals, operationalize the goals into indicators of learning, describe the environment and the data/metrics we need to collect and analyze in order to measure the learning indicators.

6.1 Defining Learning Goals and Objectives

Knowing which learning goal a learning game, or simulation, is trying to achieve is paramount to successful learning analytics. Without knowing what to track, or what represents if students are moving towards (or away from) the desired learning objective, it becomes impossible to evaluate which students are doing well and which are doing poorly, and so it is meaningless to try to evaluate whether the students are on a beneficial developmental trajectory.

Egenfeldt (2005), leveraging Bloom's taxonomy of learning (1956), defines three types of learning goals for digital learning environments: *procedural*, *cognitive*, and *affective* learning goals.

Procedural learning goals refer to learning goals where the objective is to enable the learner to carry out new procedures that they were previously not capable of doing. The concept of procedures does not suppose any deep understanding, but simply describes the capacity to carry out particular sequences of operations, whether physical or mental. Each of these skills do not require understanding of why the procedure is done the way it is, but relies on rote learning (a memorization technique) through practice until the skill is sufficiently trained. Using a flight simulator as an example, a procedural learning goal could be the ability to control a plane using the flight stick.

Cognitive learning goals refer to learning goals where the objective is to learn particular mental constructs and place them in relation to one another, and already existing constructs. An example could be to learn the concept of an ecological system, and understand how the elements of that system are interdependent upon one another and influence one another.

Affective learning goals refer to learning goals that are concerned with a learner's attitude toward particular topics. They are not preoccupied with how well a learner understands a concept or how proficient a learner is at a specific skill, but rather deals with how a learner feels about the concept or skill.

Characterizing a digital learning environment in terms of the learning goals that it pursues may be helpful to constructing a learning analytics solution for the environment. This may inform the particular features/metric that are collected from the game, it may inform the interpretative procedures that are defined for the learning environment, and it may inform the choice of modeling techniques applied for predictive learning analytics.

Obviously, a learning environment may have multiple learning objectives at all three levels at the same time. In the Go lab Wind Energy Lab, for instance, one cognitive goal may be for the student to *1) understand the connection between the wind speed and amount of the* *wind power produced by the wind turbines* while another cognitive goal may be to *2) understand that the power requirement for a city may vary over time*. An affective objective may be for the student to *3) gain an interest in green energy*.

6.2 Describing the Learning Environment

A precise characterization of the learning environment is essential for developing useful analytics. What does the simulation, or game, consists of and what are the possible actions the student can take? Being specific about these element gives us the building blocks to talk about what happens in the learning situation and we can define what learning may look like in the given environment.

Evidence centered design introduces a framework for designing, producing and delivering educational assessment and have been performed by researchers from the Educational Testing Service, Pearson and GlassLab (Mislevy, et al., 2014). Finding evidence of learning is part of the framework and refers to the act determining which actions that can prove an individual understands e.g. complex problem-solving (Mislevy, et al., 2014). We will use this part of the framework but refer to it as indicators of learning, since evidence seems like a strong word to use in this context.

Once we have described all the elements of the learning environment, we can define which events, we believe are indicators of the student approaching or reaching particular learning objectives. This could be actions, or sequences of actions, the student takes in response to a current game state or tasks giving in the learning environment. This in turn shows us which elements and actions are important to track. These actions can be referred to as *an indicators of learning* and support the notion that when the learner performs this particular action or sequence of actions, we believe they are about to reach the learning goal. If a learning goal for example is learning how to drive a bike, we might assume a gradual increase in meter driven without falling could indicate that the student is obtaining better balance, which is a key skill needed for riding a bike. Another indicator could be increased speed. However, these would need to be broken down to smaller tasks, as e.g. driving a lab on a specific course. By adding specific tasks, we can control the variables and compare the progress for one student or across multiple.

6.3 Determining metrics for learning analytics

Once the elements and interactions of the digital learning environment have been identified, it becomes possible to determine the metrics that can be tracked from the environment. In the subsections below, we provide an overview of metrics in digital learning environments. These metrics can be matched up with the identified tasks and indicators of learning. Based on identified tasks and indicators of learning, what we would need to track in order to capture the students behaviour.

First, we define *how* metrics may be collected in terms of *time* and *resolution*. Then, we describe the specific metrics that can typically be collected, drawing on the work provided in D1.2 and D2.1.

Time

Time refers to whether metrics are collected at a single point in time or across multiple related points in time. Depending on the digital learning environment being applied one point of time, multiple, or both kinds of metrics may be appropriate.

Longitudinal metrics are collected for the same individual(s) over a series of time points and allows for the observation of developments in these metrics (e.g. the bicycle example, how did the learner progress over time).

Cross-sectional metrics, in contrast, 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 (again the bicycle example, but how did one learner perform compared to the others, performing the same task).

In relation to time it is also important to determine **the sample rate** for the collection of data. Typically, tracking will occur based on event triggered by the actions of a user but in a learning environment it is important to get the full picture of what the students are reacting to. Therefore, tracking should instead be based on any important change in the environment or at a fixed time interval.

Resolution

The resolution of the data collection refers to whether metrics are collected at the individual or at the group level - typically defined by the school class interacting with a digital learning environment, though other group configurations are possible as well.

Individual-level metrics are collected from interactions performed by the individual student. Since student-level metrics can usually be aggregated into group level metrics, collecting data at this resolution is generally preferable from a learning analytics point of view and obviously essential to creating individual student profiles and models. However, this is not always possible, due to technical or practical constraints. For instance, many school settings have students sharing computers and some virtual labs may need collaboration between students for maximal pedagogical effectiveness. These situations may make it impossible to identify the interactions stemming from one particular student, in which case it may be advantageous to aggregate the collected metrics into group level observations.

Group-level metrics 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. When circumstances such as the design of a virtual lab or the concrete conditions under which the lab is used make it impossible to discern individual students in the data, group-level metrics may still be informative. They provide the option of looking at patterns in interactions across the group as a whole and allows for comparing one group to another. In case of school classes, for instance, it may be helpful to a teacher to know that one class is performing differently from another class, and the teacher may adjust their pedagogical strategies accordingly.

Metrics

Based on the input from the educational subject matter, several metrics were defined in D1.2 and D2.1 as relevant for learning analytics. We will concentrate on time-on-task, time-to-completion and travel-path since these metrics lie within the scope of shallow analytics.

Time-on-task describes how long an individual spends engaging with a single task in the virtual lab. The designer of the virtual lab must define the task itself externally and specify the associated signifiers of the start of a task and the end of 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 because of a user action or as a consequence of a state change in the virtual lab, driven by the simulation itself. Time-on-task, then, is calculated as the real-world time difference between the defined end-time t_{end} and the defined start-time t_{start}.

Time-to-completion

This metric is similar to time-on-task but the main difference is the emphasis on measuring the overall time spent from the start of the whole sequence of tasks until the completion of the last task that, the learning activity consists of. Time-to-completion is thus a composite of time in a sequence of tasks. Time-to-completion is therefore also calculated as the difference between the defined end-time t_{end} and the defined start-time t_{start} but will consist of multiple tasks.

Travel-path related metrics

Travel-path is related to a sequence of actions that a learner performs e.g. within a virtual lab. An example could be the overall length of the sequence students take or focus on critical path to completion. The measure can be used to map the multiple sequences of action taken to solve a specific task. When clarifying how individual students solve tasks, profiling based on paths can subsequently be performed.

7 Prototype and Shallow analytics in the Wind Energy Labs

This section focuses on applying the concepts and definitions of learning analytics, presented above, to the wind energy lab. The section starts out with defining the type of learning the lab facilitates, then moves on to defining the actual learning goal, the learning environment will subsequently be defined, and lastly, the metrics needed to track the indicators will be determined and related to the two versions of the wind lab.

The data collected in the original GoLab Wind Energy Simulation as described in D2.1 will be used in the prototype that accompanies this deliverable to illustrate how the shallow analytics metrics are calculated.

To further exemplify the concepts presented in section 6 this section will also propose how to work with future data from the 3D Wind Energy Lab where the tracking will be enhanced to include the game state and more accurate user logging.

7.1 Learning goals in the wind energy labs

The section will describe which types of learning goals the labs facilitate.

Neither of the labs can be said to have procedural learning goals that are transferable to relevant contexts outside of the two simulations.

The labs could be said to contain affective learning goals related to wind energy as the subject such as inspiring the students to learn more about wind energy or develop an interest in clean energy. But neither of the labs state this type of goals as clear purposes of labs.

Both labs focus on cognitive learning goals. As stated earlier, learning environments can have multiple objectives or learning goals at the same time. The following is an incomplete list of some of the cognitive learning objectives one can observe in both wind labs.

- To understand the connection between the wind speed and amount of the wind power produced by the wind turbines.
- To understand that wind speed varies throughout a day.
- To understand the connection between the number of active wind turbines and the amount of wind produced.
- To understand that wind turbines may break.

For the learning goal “*To understand the connection between wind speed and amount of the wind power produced by the wind turbines”* students in both wind labs should be able to manipulate the wind speed and maintain the status “correctly powered” in most of the simulation and thus fulfilling the objective of the lab.

7.3 The Wind Labs as Learning Environment

This section will briefly describe the learning environment of the virtual labs with an overview of the labs and the variables that may change either directly or indirectly because of the students’ interaction or just as a part of fluctuations in the simulations.

GoLab Wind Energy Simulation

In the Wind Energy lab, the student moves freely between the areas Home, Instructions, Configuration, Simulation and Report Chart. Home is the entry page. Instructions describes the simulation and hosts educational reading material on different taps. Configuration is where the students can configure the different elements of the simulations; Wind speed, number of turbines, power requirement and select the simulation speed. Simulation shows the output of the simulation with the option of pausing, starting or resetting it as well as adding or removing turbines. Report Chart shows the result of the simulation with the choice of seeing the result in pie chart or in an hourly report. When the simulation is running, the student can only influence the simulation by adding or removing turbines. To change e.g. the wind speed the simulation must be reset.

The trackable actions

- Click on Home
- Click on Instructions
- Click on Configuration
- Normal speed, fast speed and warp speed
- Click on Simulation
- Add and remove turbine
- Start/restart, pause and reset simulation
- Click on Report Chart
- Show power output report/show power pie chart
- Show values for simulation/Show values for current hour

The collected data does not include game state information such as the configuration settings, the current simulation values or the simulation status.

3D Wind Energy Lab

The 3D Wind Energy Lab is a re-designed version of GoLab Wind Energy Simulation and has been subjected to the same design process as labs would be when using the authoring tool, which is data driven.

This lab will have more tracking available including tracking of the entire game state which will make it possible to see the change in the learning environment the student's actions may be reaction to.

In the 3D Wind Energy Lab, the student is shown a 3D landscape where wind turbines can be placed. The student has access to a configuration panel where wind speed and wind requirements can be changed, the changes will affect the simulation in real time. The following is a list of elements that may be tracked.

Variables

- Maximum number of wind turbines
- Minimum number of wind turbines
- Maximum wind speed
- Minimum wind speed

- Maximum power requirement
- Minimum power requirement
- Power status (overpowered, underpowered, correctly powered)
- Game time

Game state

- Number of broken wind turbines
- Current wind speed
- Current power requirement
- Current power production
- Current power status (overpowered, underpowered, correctly powered)

Actions

- Close instructions
- Open configuration panel
- Close configuration panel
- Place windmill
- Turn off windmill
- Repair windmill
- Set minimum wind speed
- Set maximum wind speed
- Pan view

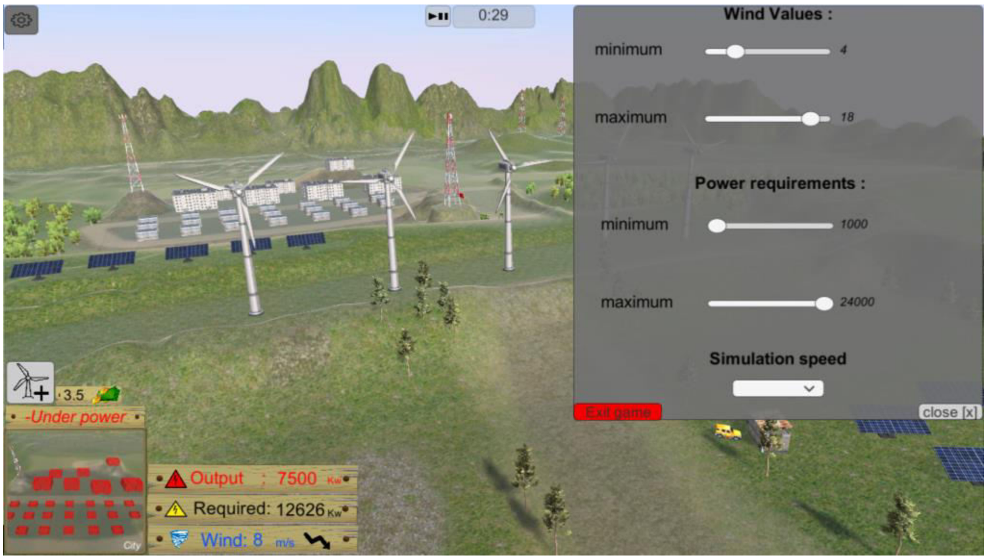

Figure 1: Screenshot form the 3D Wind Energy Lab, showing the current power status, produced output, required output and the wind speed. In the top right corner, the max and min values for the variables; Wind values and Power requirements can be adjusted.

7.4 Indicators of learning

Based on the learning goal and the description of the learning environments presented above, we will propose possible actions, which could be indicators of learning in the two versions of the wind energy lab. Furthermore, we will also define what a possible task within the labs could be.

Since the learning goal is defined as, "understanding the connection between the constructs wind speed and amount of energy produced by the wind turbines" and the aim of the labs is to stay correctly powered as much as possible, a task in the labs could be changing the game state from over- or underpowered to correctly powered. Solving this task would thus indicate an understanding of achieving correct power by adjusting e.g. wind speed or amount of wind required.

The labs show the time the users have obtained over-, under-, or correct power. If we still see a task as "changing the game state from over- or underpowered to correctly powered" another indicator of learning could be the time spent on performing the task, meaning the time it takes from under- or overpowered until the town is correctly powered once again. The assumption is that if I solve the task faster I have mastered the balance between the variables and therefore solve the tasks faster as a result.

The last indicator of learning presented here is the sequence of actions, which is used to solve the task. If the user is, e.g. in overpowered state and continues to add more wind turbines, this action shows a misinterpretation of the task and the constructions within the lab. However, the user might realize this and as a result turn off wind turbines until the power status is "correctly powered" again. The user has solved the task but used another sequence of actions than a user who immediately turned up the required power of or turned down the wind power. If we assume that user who performed the shortest path of actions has obtained a deeper understanding of the lab, the indicator would be the specific path chosen to solve the task.

7.4 Metrics

This section will present how the three metrics, we focus on for the shallow analytics, are calculated. First, the prototype, built on data available from the GoLab Wind Energy Simulation, is described. Then the ideas for working with the re-designed 3D Wind Energy Lab with enhanced tracking are exemplified with synthetic data.

Metrics in prototype

As described in D2.1 the data collected from the GoLab Wind Energy Simulation is event-based. Each tracked event is saved with multiple values such as event name and device type. For the purpose of the prototype, only the event values that indicate the event name, the timestamp for when the event was triggered, the user identifier as well as meta data identifying the location are used.

The event name and timestamp is used for calculating the three metrics: Time-on-task, time-to-completion and travel path. For this initial prototype, the identifier is used to illustrate individual users but it is worth noting that in the case where e.g. multiple students use the same account on a computer to access the wind lab the user identifier may not distinguished the students. The data related to locations is used in the prototype to show the potential in filtering users.

Before splitting the raw event data into the structure used to calculate the metrics, we first ordered it by user chronological.

Time-on-task

The event tracking in the GoLab Wind Energy Simulation allows us to determine when a student moves from one event of the lab to another. So, in this lab a logical delineation of time-on-task is to look at the time spend in each events as separate tasks. For each event, the time-on-tasks t_{start} is thereby defined by the point in time when the student triggers an event. The point in time when the student triggers another event defines t_{end}.

This metric does not include a performance measure so evaluating the importance of how much time a student has spent on the different event as an indication of learning is up to the individual teacher to determine.

Time-to-completion

For the time-to-completion metric in the prototype, we define it as the length of a play session and it is as such an aggregated measure for the time spent on all the tasks in a play session.

For each individual user t_{start} for a session is marked by a launch event and t_{end} is defined by either the next launch event for that user or the last event triggered by the user. There is no information, in the data, to determine when the user leaves the lab so the beginning of the last event is therefor used to define when the player stops using the lab.

As with the time-on-time described above time-to-completion does not include any intrinsic performance measure so it is entirely up to the teacher to determine how this metric can inform design changes.

Travel path

For travel path, the prototype uses the calculation derived from the two previous metrics and simply orders the tasks in the order they occur in user's play session.

The travel path provides an overview of which parts of the lab the student has interacted with over the course of a play session. Allowing the teacher to see if there are parts of the lab the student may have overlooked or spent a larger amount of time on. Again, the data does not have any defined measure for calculating the students' performance in relation to the travel path there is no indication of whether one sequence or actions is preferable to another so it is up to the teacher to read this into the metric.

Timeline visualization

All three metrics, explained above, are included in one timeline visualization, which is described in detail in D2.3.

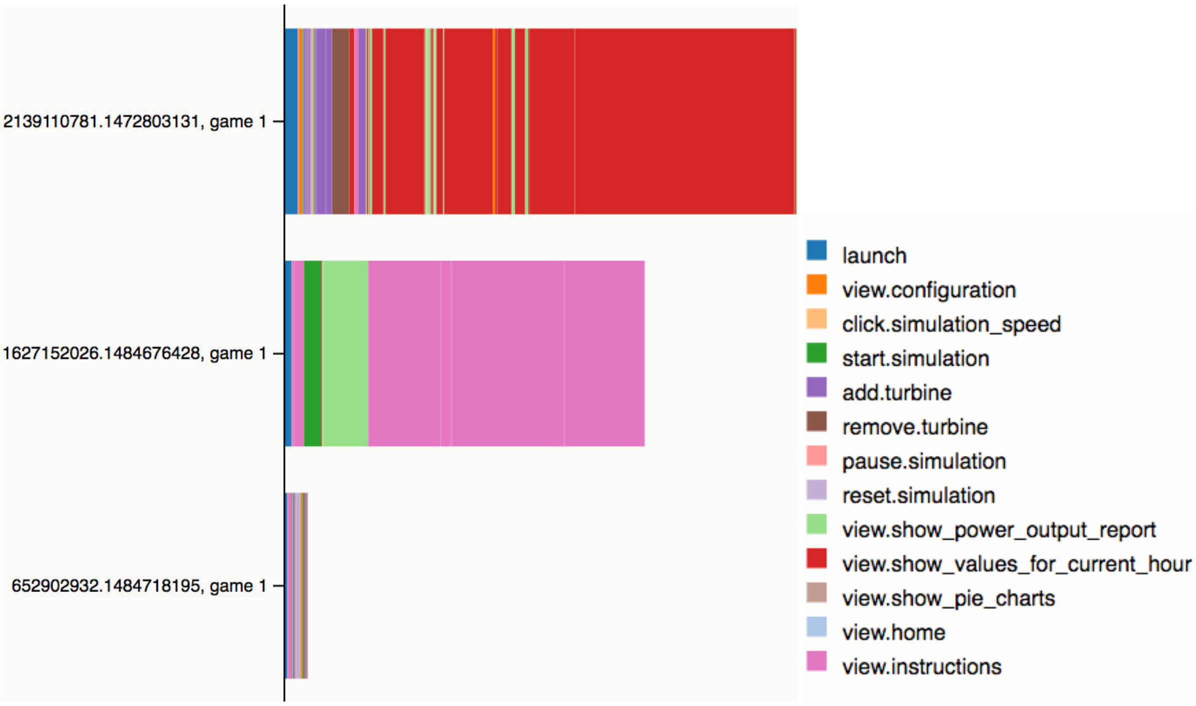

Figure 2: Screenshot of part of the timeline visualization that combines the time-on-task, time-to-completion and travel-path into one. The selection shows the data from three users from Jan 02 2017 11:32:57 GMT+0100 (CET) to Jan 22 2017 00:06:36 GMT+0100 (CET).

Metrics in 3D Wind Energy Lab

The three metrics proposed for the 3D Wind Energy Lab, and examples of calculation using synthetic data, will now be presented.

Time-on-task and time-to-completion

To work with the metrics time-on-task and time-to-completion, we need to define what constitutes a task or tasks within the context of the wind lab and when tasks are defined as completed.

We can define the entire wind energy lab as one task where t_{start} and t_{end} are defined by the time the student launches the wind lab and the time the student either quits the simulation or the game time is up. However, in this case the t_{end} merely becomes a function of whether the student chose to interact with the time controls in the simulation either accelerating or pausing the game time. Isolated, time-on-task may be hard to use for informing a design change but if we combine it with a performance measure, it may become a more valuable indicator of learning and the designer will have more information to make an educated analysis of the data.

Table 1. below, illustrates how we can evaluate three students' performances over three play-throughs by combining the time-on-task metric and the percent of time the power status is correct. In this example, all three students improve their performance over time.

Table 1: illustration of the evolution of three students' performances over three play-throughs and by combining the time-on-task metric with the percent of time the power status is correctly.

StudentID	Time-on-task (Game speed)	Normal speed/Time-on-task	% of time correctly powered	Performance
1	24	1	20%	0,2
1	30	0,8	50%	0,4
1	8	3	80%	2,4
2	24	1	20%	0,2
2	16	1,5	30%	0,45
2	16	1,5	80%	1,2
3	24	1	30%	0,3
3	8	3	60%	1,8
3	8	3	70%	2,1

There are currently no predefined subtasks built into the wind energy lab. Nevertheless, if we want to look at the simulation in finer detail we could, for instance, see the power status from the game state as a proxy for tasks the student may respond to. Every time the power status is underpowered, or overpowered, the student is faced with the task of reaching the correct power. For these subtasks t_{start} would be defined by the point in time when the power status changes from correctly powered to either underpowered or overpowered with the exception of the beginning of the simulation when the status always underpowered. The point in time when the power status changes to correctly powered will define t_{end}.

The table below show a fictive example data set for one student where each change in the environment is tracked as an event. Events based on the student's actions are marked in bold. For the sake of simplicity, we only show the studentID, timestamp, power status and event. A real dataset would naturally contain more details.

Table 2: The table illustrates how subtasks based on the power status could be delineated.

Student Id	Timestamp	Event	...	Power status
1	08.53.00	launch		underpowered
1	09.00.00	**close.instructions**		underpowered
1	09.00.13	change.power_output		underpowered
1	09.01.19	**add.windmill**		underpowered
1	09.02.32	**add.windmill**		underpowered

1	09.02.55	change.wind_speed		underpowered
1	09.03.15	**add.windmill**		underpowered
1	09.04.20	**add.windmill**		correctly_powered
1	09.04.30	**add.windmill**		overpowered
1	09.04.48	change.wind_speed		overpowered
1	09.04.53	change.wind_speed		overpowered
1	09.05.06	**open.configuration**		overpowered
1	09.05.21	**set.wind.max**		overpowered
1	09.06.26	**set.wind.min**		correctly_powered
1	09.06.30	change.power_output		correctly_powered
1	09.07.03	**close.configuration**		correctly_powered
1	09.07.55	change.wind_speed		underpowered
1	09.08.01	**add.windmill**		underpowered
1	09.08.14	**repair.windmill**		underpowered
1	09.09.57	change.wind_speed		correctly_powered
1	09.10.04	**open.configuration**		correctly_powered
1	09.10.16	**click.simulation_speed**		correctly_powered
1	09.10.47	change.wind_speed		correctly_powered
1	09.11.01	change.power_output		correctly_powered
1	09.11.31	change.wind_speed		overpowered
1	09.11.51	**turn_off.windmill**		overpowered
1	09.12.08	change.power_output		overpowered
1	09.12.37	change.wind_speed		overpowered
1	09.13.05	change.wind_speed		correctly_powered
1	09.13.25	result_screen		correctly_powered

In this case the student spent, in addition to 7 minutes (420 sec) spent on the instructions, a total of 13 minutes and 25 seconds (805 sec) in the simulation. This time, the student had 4 periods of not being correctly powered and roughly correctly powered 27% of the time. The table below gives an overview of the different time-on-task for the subtasks.

Table 3: an overview of the time-on-task for the subtasks.

Subtask	t_{start}	t_{end}	Time-on-task	Time-on-task in sec
1	09.00.00	09.04.20	4min 20sec	260
2	09.04.30	09.06.26	1min 54sec	114
3	09.07.55	09.09.57	2min 2sec	122
4	09.11.31	09.13.05	1min 34sec	94

Looking at multiple tasks, and in this case very similar tasks, gives us the opportunity to calculate an average, mean or variance for the students' time-on-task and to look for any trends in how the time-on-tasks develops over time. This could be seen in relation to other students' performance and classes as a whole. Again, seeing the time spent on the tasks in relation to the amount of time the simulation is correctly powered could give a performance measure. In this indicative example, it appears the student is becoming faster at solving the problems as they occur in wind lab. This could be seen as an indicator of learning.

We can also look at different tasks in relation to each other and use that as our indicators of learning. In our example, the students can spend time on two different tasks. One is adjusting variables in the wind simulation the other is reading the instructions for the wind lab. From data, we cannot know if the time spent on the instructions is actually spent reading the instructions and learning through text about wind energy. If we were using an eye-tracker, we could see if the student's eyes were moving along the lines in the text and if they were resting on particularly difficult words or passages but it would not tell us about the student's level of comprehension. A teacher or educational designer might give a range for what they believe is an appropriate amount of time to spend on the instruction but again this will not necessarily infer comprehension. However, if we look at the time spent on the instruction in relation to the time spent in the simulation and the student's performance we may see a pattern in the comprehension emerge.

Travel path

Investigating the sequence of actions the students take in the wind lab is also a way of profiling the students. We can imagine how some students might explore all actions in the simulations while others might settle on only using a few of the possibilities in the sandbox environment. Combined with our previous performance measure, we may even identify strategies in patterns of actions.

For the subtask we defined earlier, we can even define sets of actions that are normatively better than others are and compare the student's action to these. For instance, if the city is underpowered it is better to add a windmill than turning one off. The game tree below show a subset of the actions a student can take when dealing with the task of an underpowered city and the normative outcome of the actions. For a similar subset of action for an overpowered city, the outcome is naturally the reverse.

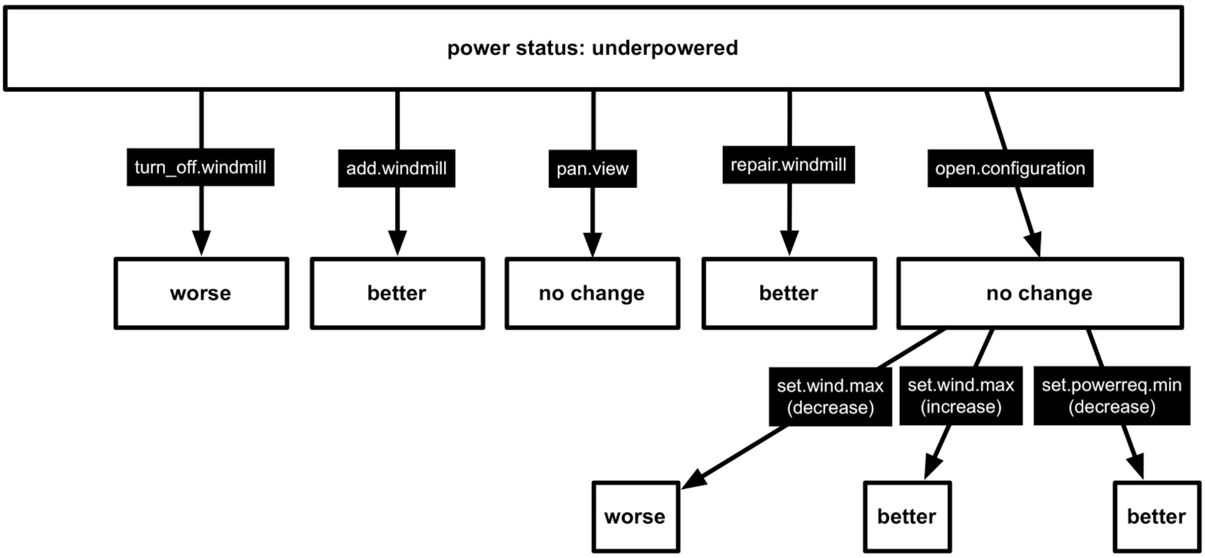

Figure 2: Decision tree, illustrating the outcomes of the different actions the students can make when the status is overpowered.

If we compare student's actions, as seen below, to the possible actions, as represented in the game tree, we find that all the actions taken by the student either kept the game at status quo or improved the game state, moving it closer to the desired state. We might see the student's ability to continuously choose the right strategy as indication that the student has understood the connection between the different elements of the simulation.

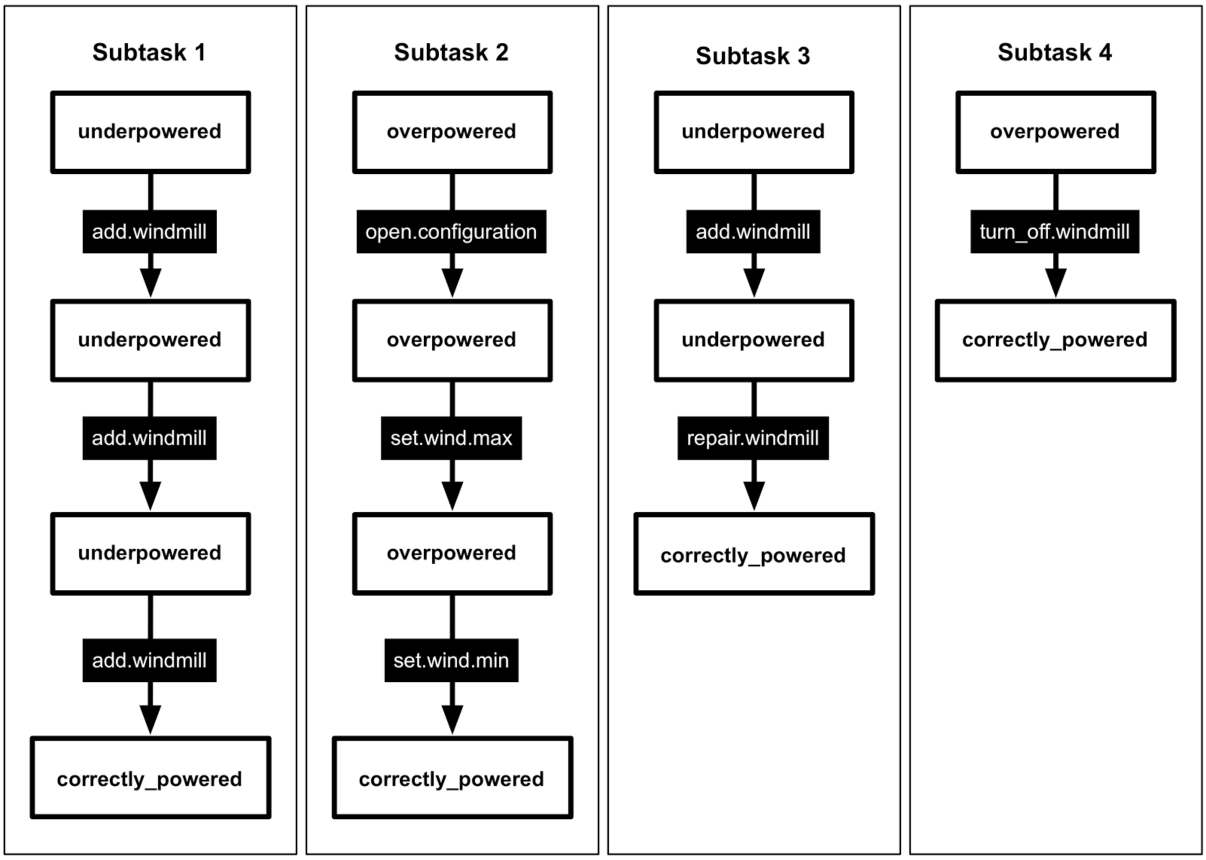

Figure 3: Overview of the travel-paths a single student used to solves the subtasks over- and underpowered during a simulation.

In order to quantify this strategic understanding we can count the number of correct steps a student takes and evaluate each state in the sequence of actions. The ability to choose different strategies to solve the same task could also be seen as beneficial or at the very least as part of the student profiling.

8 From Metrics to Profiles in ENVISAGE

This section leverages the principles derived in Sections 4 to 5, and the metrics described in detail in Sections 6 and 7 to define profiles of students and classes in the Wind Energy Labs.

We define profiles as collections of data describing the same individual, or groups of individuals, over the course of one of more gameplay sessions. While the basis for a profile are the recorded metrics described in Section 7, the raw metrics over time themselves do not constitute the profile. Rather, profiles are determined by values aggregated from observations of the metrics over time, from a least one session and updated when, or if, multiple sessions are recorded.

Profiles serve the purpose of characterising and comparing individuals, or groups, with other individuals, or groups, and provides long-term representations of these. In the wind energy labs, the profiles of individuals are determined by the three metrics:

- **time-on-task**
- **time-to-completion**
- **travel-path**

From the travel-path, we can additionally calculate a metric of the average edit distance between recorded travel-paths within an individual (if we have login data) or within a group of individuals that co-occurs in time or place.

Additionally, the profile contains the collected meta-data:

- **Unique browser ID**
- **Location (based on IP address)**

Group profiles, used to identify e.g. classes, need the same metrics, but additionally add the

- **start time**
- **end time**

of the individuals' gameplay sessions, allow for grouping into classes interacting with the Wind Energy Labs at the same time.

While not currently a capability in the Wind Energy Labs, profiles should also be defined by their persistent and unique

- **studentID**

as described in Section 7.

These metrics will then be aggregated in the manner described in Table 1.

Table 4: List of metrics currently included in a profile in ENVISAGE and how the profile values are calculated from each metric.

Metric	Integration in Profile
Student ID	Static across sessions
Start-time	No aggregation, saved as list of timestamps

End-time	No aggregation, saved as list of timestamps
Time-on-task	Mean time for each task type.
Time-to-completion	Mean time for each session.
Travel-path	Travel-path as string.
Travel-path distances	Mean edit distance between all travel paths in the same virtual lab.

These profiles may later be enriched with the same or additional metrics from additional labs in the ENVISAGE project. For metrics that occur in multiple labs, these should be calculated both for the individual labs and normalized across all the labs for which the profile has data.

Once Deep Analytics provides values for the individual users, or groups, these values should be added to the profiles too. As such, the above definition of a profile should be considered preliminary and will be expanded over the course of the ENVISAGE project.

At the time of writing, all metrics that constitute a profile are provided by the shallow analytics library contained in `envisage_shallow.js`. These values are compiled and calculated just-in-time in the user's browser from the raw observational data and are not stored between requests. This is possible and unproblematic due to the high-performing data selection and delivery made possible by the goedle.io service. In the event that profiles are expanded with more intricate metrics, or that datasets defining individuals or groups grow large enough that large lists of sessions and metrics describe each profile, it may become necessary to calculate these values off-line and store them separately in the goedle.io service.

9 Conclusion

As clarified in the sections above, the nature of the lab or learning game, determines which elements should to be tracked and which metrics can be utilized and inform the profiling of students.

For this deliverable, we have so far concentrated on shallow analytics and profiling based on the wind energy lab. Going forward, we will be able to expand the work to include additional labs. Adding more labs will naturally increase the relevance of the profiling, while it may also reveal the need for defining additional metrics

For the wind energy lab, predictive analytics and profiling are possible if the sample size is large enough. However, since the data we have gathered is only from the wind energy lab, we are only able to draw conclusions within this particular lab at the moment but more lab are currently being setup for tracking. Predictive analytics focused on predicting e.g. future performance outside of the Wind energy lab, is thus not possible with telemetry from one-time use of the wind lab, as we do not have any information about how the students perform in the future, unless it is reported later or the students revisit the lab. However, revisiting the lab would be problematic, as we could probably expect the students to perform better the second time they use the lab, as they would be playing towards the same goal and the same variables. If the students already know the connection between the variables, the learning objective we are measuring would be their understanding of the specific relationship between the two variables, wind speed and produced energy. Instead, a long-term learning goal would be the student's overall cognitive abilities to recognize patterns and understand variable condition for problem solving. If a longitudinal dimension is added and the students now revisit the lab but simulating new scenarios that e.g. increase required skills-level and challenges, it might be possible to conclude on their overall problem-solving abilities and even predict how their learning progress over time through the different scenarios.

Only having data from a single use is therefore restricting what can be derived from the lab. The addition of supplementary labs, using the same, or additional, metrics from others labs within the ENVISAGE project will offer enable utilizing more advanced analytics for profiling and behavioural modelling.

Having multiple data sources is key if we want to be able to predict and profile beyond a single lab. This is essential, as students and teachers are already assessed to be making the most precise prediction of long-term performance (Hattie, 2009) and to provide additional value, learning analytics needs to go beyond this. Having data from multiple students, having used multiple labs could be one way of acquiring more data sources and providing broader analytics. The deep analytics can provide a higher value for the individual users, or groups of users, as the additional data being added to the profiles will facilitate more extensive profiling.

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