



# Electronic Portfolios Enhanced with Learning Analytics at the Workplace

# 76

Marieke van der Schaaf

## Contents

Introduction .....	1410
Background: ePortfolios and Learning Analytics .....	1412
Component 1: Domain Modeling – Entrustable Professional Activities as Units of Professional Practice .....	1413
Component 2: Task Model – Information Sources to Provide Evidence for Entrustability .....	1415
Component 3: Evidence Model – Development of a Student Model-Driven Probabilistic Approach .....	1415
Component 4: Presentation Model – Development of Written and Visual Feedback .....	1416
Written Feedback .....	1417
Visual Feedback .....	1418
Component 5: Evaluation .....	1420
Conclusion .....	1424
References .....	1425

## Abstract

During workplace-based learning, e.g., clinical or during an internship, supervisors' quality of feedback and assessment is crucial for trainees' expertise development. Electronic portfolios (ePortfolios) are often used as tools for longitudinal assessment at the workplace. So far, ePortfolios have not realized their full potential, since they are often not well tailored to the workplace and trainees' needs. Potential data about trainees' behavior at the workplace is generally underused, and the management of the data is complex. It is expected that ePortfolios enhanced with learning analytics may serve as means to improve

---

M. van der Schaaf (✉)

University Medical Centre Utrecht and Utrecht University, Utrecht, The Netherlands

Center for Education and Department of Education, Utrecht University, Utrecht, The Netherlands

e-mail: [m.f.vanderschaaf-5@umcutrecht.nl](mailto:m.f.vanderschaaf-5@umcutrecht.nl)

© Springer Nature Switzerland AG 2019

1409

S. McGrath et al. (eds.), *Handbook of Vocational Education and Training*,  
[https://doi.org/10.1007/978-3-319-94532-3\\_89](https://doi.org/10.1007/978-3-319-94532-3_89)

the quality of feedback and assessment regarding trainees' progress and development. This chapter addresses this by outlining an approach that is applied in a European 7th framework project ([www.project-WatchMe.eu](http://www.project-WatchMe.eu)).

This chapter shows the development of an ePortfolio environment enhanced with learning analytics, to be used at the workplace in medical, veterinary, and teacher education. Evaluation took place by means of a quasi-experimental design regarding the impact of this environment on trainees' motivation, their assessment experience, and their use. Data gathered in four institutes for medical, veterinary, and teacher education ( $n = 217$ ) showed that trainees were highly motivated for their internships and positively evaluated the perceived feedback. The use of learning analytics features varied. In general visual feedback by means of a timeline of trainees' progress was mostly used, while trainees barely used the features with written feedback. It is concluded that the promise of learning analytics connected to ePortfolios can only be fulfilled when developed and implemented through the eyes of the users.

---

**Keywords**

ePortfolio · Learning analytics · Workplace · Feedback

---

## Introduction

Work in professions is increasingly driven by reflection, feedback, and collaboration with a decline in the number of desk workers and a rise in flexi-workers who tend to work at multiple locations. This urges the need for learning data, feedback, and visualizations to be made accessible anywhere at any time through mobile devices. Furthermore, there is an augmented need for accountability and certification in most professions, which has led to a compelling need for valid authentic assessments. Recent growth in the use of electronic portfolio environments (ePortfolios) and the increasing use of mobile devices (e.g., tablets and smartphones) at the workplace have further stimulated the demand for an advanced ePortfolio environment based on learning analytics. ePortfolios are purposeful digital collections of a learner's work, including their reflections, that provide evidence for their performance and progress (Butler 2006; Rezgui et al. 2014). They demand a learner's reflection on personal data and progress within the social cultural work context of the learner (Butler 2006; Dysth and Engelsen 2011). Learning analytics is defined as the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purpose of understanding and optimizing learning (Elias 2011). Learning analytics can add to ePortfolios the modeling of learners' expertise development in order to provide automated feedback, intervene during learning processes (e.g., by sending alerts), recommend tutoring, and so on.

Meanwhile, learning in professions is shifting from an educational setting to a workplace setting, both within and outside schools (Billet 2004). Learning at the workplace is domain specific and includes an adaptation to constantly changing task demands (Feltovich et al. 2006). A concept that is important for understanding and

explaining the development of expertise in professions is deliberate practice. Core assumptions of deliberate practice are that expert performance is being acquired gradually and that effective improvement of performance requires the opportunity to find suitable training tasks that the performer can master sequentially (Ericsson et al. 2006). Key to deliberate practice is frequent feedback based on adequate analyses and evaluations of how tasks at the workplace are fulfilled. Although the concept of deliberate practice is less applicable to complex professional contexts without standardized tasks, such as teaching (Ericsson and Pool 2016), it emphasizes the importance of feedback and assessment on activities of (becoming) professionals as the most powerful sources for learning at the workplace.

Workplace-based feedback and assessment demands valid ways of dealing with unique (personal) multimodal data from a variety of sources gathered at unstandardized work contexts, over a longer timespan. Effective feedback provides learners with (1) insight into obtained performances compared to an expected norm, (2) the possibility to evaluate and monitor the own process, and (3) suggestions to bridge the gap between the expected norm and the actual performance (Sadler 2010). Feedback can support learners' development when it gives information about the goals the learners strive for, the progress that they made toward these goals, and the actions and practices to be undertaken for further improvement (Hattie and Timperley 2007). Essentially, this demands a process of drawing inferences about learners' performance and progress and feed this back, based on multisource datapoints in time (Toulmin 2003; Kane 1992).

To this end, since the 1990s ePortfolios are often used as tools to collect data and evidence about learners' development at the workplace. They include authentic products and performances, which are often seen as prerequisite for a valid assessment (Eynon et al. 2014; Peacock et al. 2011). ePortfolios can provide a supervisor with a timely overview, regardless of one's location, of learners' work over a larger timespan. They can serve as a reflective "log" of the learner including a repository of evidence demonstrating personal progress and performance (Van der Schaaf et al. 2008). ePortfolios can be used for formative goals, e.g., in terms of a developmental portfolio or reflective portfolio, or for summative purposes, e.g., a showcase portfolio. Formative assessment goals focus on providing input to a learner's further development. Summative purposes strive for high-stake consequences, such as graduation or merit pay. To fulfill ePortfolios' promises, a reflective pedagogy is needed to stimulate learners to compose a portfolio and to use it in conversations with peers and supervisors (Barbera 2009; Hamp-Lyons and Condon 2000; Van der Schaaf et al. 2012). The implementation of ePortfolios is often challenging, due to data management and implementation problems (Van Schaik et al. 2013). Consequently, potential data about learners' development in the workplace is often underused.

This chapter presents examples and experiences from a European project that aimed to improve the efficiency and quality of workplace-based feedback and assessment by means of learning analytics that is added to an existing ePortfolio environment. The project focused on the professions of medicine, veterinary medicine, and teaching, because in these domains, workplace-based learning has a central role.

## Background: ePortfolios and Learning Analytics

From a technical perspective, ePortfolios include (i) the storage of learners' artifacts or evidence (i.e., their asset repository), (ii) a presentation space where the learner can present him or herself in relation to the learning goals needed to be achieved and based on artifacts selected from the asset repository, and (iii) a feedback and reflection space where the learner and others can comment on the development or work delivered by the learner. Most ePortfolio environments include tools and services on top of this basic system, for instance, providing visualizations of a learners' progress, planning tools, or tools to include or add files as an input to other external systems (e.g., student information management systems). An ePortfolio's evidence can, for instance, include artifacts (regular products of a learner's work), reproductions (registrations of a learner's regular work, captured on behalf of the portfolio), attestations (records of a work made by others), or productions (documents prepared specially for the portfolio) (Barrett 1998; Van der Schaaf et al. 2008). An extensive amount of entrepreneurial ventures provides ePortfolio environments, stand alone or web-based. Besides, many organizations use existing digital systems that include tools with the potential for learners to capture and present evidence about their expertise development and to build an ePortfolio from that. Some examples are existing functionalities in learning management systems, web tools, tools in Blackboard, Wiki portal, PebblePad, OneNote, Microsoft Office, WordPress, and Webfolio.

Although the use of ePortfolios is widespread, the effects of ePortfolios on learners' performance are unclear and depend on how (well) the ePortfolio is used (Bryant and Chittum 2013; Eynon et al. 2014; Kennelly et al. 2016). In the last years, there has been an increase in efforts and evidence that support the promise of ePortfolios to impact on student learning and student success. Examples are shown in the *Handbook of Research on ePortfolios* (Jafari and Kaufman 2006) and the *International Journal of ePortfolio*, as well as the launch of ePortfolios as the 11th High-Impact Practice by the Association of American Colleges and Universities. Recently, several initiatives to improve ePortfolio assessment show promising results for feedback and assessment in terms of flexibility, interaction, and immediacy (e.g., Warren Lee Najmi 2014; Doyle Garrett and Currie 2014).

An upcoming approach in ePortfolio research is to connect ePortfolio environments to learning analytics to improve the efficiency and quality of workplace-based feedback and assessment. A main aim of learning analytics is to provide timely and relevant feedback to learners regarding their progress and learning (Siemens and Gašević 2012). Connecting learning analytics to ePortfolios parallels the so-called content analytics: "Automated methods for examining, evaluating, indexing, filtering, recommending, and visualizing different forms of digital learning content, regardless of its producer (e.g., instructor, student) with the goal of understanding learning activities and improving educational practice and research" (Kovanović et al. 2015, p. 78). Content analytics implies a human process of capturing a learner's performance and products to produce data that can be used

to make inferences linked to evidence that support claims about learners' expertise. An example of an inference is that data about the learners' performances need to be linked to assessment and feedback scores. This demands the alignment of a statistical model with a substantive theory regarding expertise development in the profession.

Today's leading approach of assessments based on multimodal data is Mislevy's evidence-centered design (Mislevy et al. 2012). Inspired by Toulmin's (2003) argument-based approach, Mislevy provides an architecture for the (re)design of assessments consisting of the components: (1) domain model, (2) task model, (3) evidence model, and (4) presentation. Between the components an assembly phase is centered that connects all components. The components are strongly linked. Validity evidence is needed for each component, the links between the components, as well as for the whole design (evaluation). The *domain model* determines the constructs to be measured (e.g., trainees' expertise) and describes how the constructs develop. The *task model* involves the choice of essential tasks (e.g., developing a lesson plan) and the exact key environment (e.g., classroom) needed to get information about the constructs (e.g., trainees' expertise). It also contains specifications of the type of ePortfolio environment and learning analytics required, for example, characteristics of the stimulus material (type of artifacts to be gathered), given instructions, affordances, etc. The *evidence model* focuses on the question: What counts as evidence of learners' expertise and how do we interpret this evidence? In this phase, learners' scores and interaction with the ePortfolio environment are analyzed for psychometric quality (e.g., validity and reliability) and usability (e.g., mouse clicks, time spent on certain features in the display). This data can be used to determine whether and to what extent the existing scoring rules and features of the ePortfolio environment should be adjusted. The ePortfolio environment including learning analytics will be finalized in its *presentation* form. During the whole design process, a close cooperation between educational specialists and computer scientists is key in order to obtain effective solutions. Next, evaluation of the implemented prototype needs to be carried out. Below are the components that were followed in the project that is central in this chapter. The components can be seen as an example of how to connect learning analytics to an ePortfolio environment.

---

### **Component 1: Domain Modeling – Entrustable Professional Activities as Units of Professional Practice**

The development cycle starts by gathering the necessary information from educational theories, research, and specialists into the development of learners' expertise at the workplace. Learning at the workplace is domain specific. In the past decades, competency-based frameworks were designed to restore the quality and structure of workplace-based education. The frameworks generally related to a competency-based approach, describing the knowledge, skills, and attitudes of professionals,

needed to carry out specific professional tasks. Examples of such frameworks are the Canadian CanMEDS framework in medicine (Frank 2005), the VetPro competency framework for the veterinarian domain (Royal College of Veterinary Surgeons 2014), and national teaching standards in many European countries.

So far, the concept of competencies has met with mixed success. This is partly due to unclarity of the concept and its operationalization of the concept in long (analytical) lists of subcompetencies. Essentially it is important to bring the concept of competencies back to the primary process of work of professionals (Mulder 2014). According to this idea, in 2005, the concept of Entrustable Professional Activities (EPAs), i.e., tasks or responsibilities to be entrusted to the unsupervised execution by a trainee once sufficient specific competency is obtained, was designed to link competencies to performances in the medical workplace (Ten Cate 2005). The focus of EPAs is not only about the evaluation of a learner's ability but implies an estimation of how much supervision a learner needs at the workplace, i.e., how autonomously the learner can carry out professional tasks. A crucial underlying question regarding EPAs is: would I entrust this trainee unsupervised with this task (e.g., with my sick mother) or, in teacher education, with teaching my daughter or son? Examples of EPAs are conducting patient handovers; anesthetic management of a patient; conducting a normal, low-risk delivery; and interviewing adolescents regarding high-risk health behavior. Levels of entrustment that go with EPAs are: acting is not allowed, more observation is needed (*low level*), and up to acting is allowed "unsupervised": under clinical oversight, distant/backstage supervision, or post hoc report (*high level*) (Ten Cate 2005). Originated in medical education, EPAs have now been applied also in allied health programs (e.g., nursing, physician assistant education, midwifery) and other programs. In teacher education the concept of EPAs comes close to the concept of Core Practices, i.e., the most crucial professional activities of a teacher's daily work (Grossman et al. 2009). In this chapter we use the word Core Activities instead, to describe teachers' work in practice.

The internationally emerging concept of EPAs is fundamental to define the criteria for workplace-based feedback and assessment. In the project underlying this chapter, a series of Delphi studies and focus groups was carried out to collect data among experts and trainees for health professions education and for teacher education to develop ready-to-use EPAs and Core Activities (Wisman-Zwarter et al. 2016; Duijn et al. 2017; Jonker et al. 2015; Leijen et al. 2017). These were described in rubrics to be useful for assessment purposes. A rubric is a description of aspects of work with associated performance level descriptions (Dekker-Groen et al. 2012). The development of rubrics showed clear differences in context and methodology between different professions. For instance, the healthcare context (medical and veterinary) is characterized by a large variety of short encounters between trainees and various supervisors and other healthcare staff. The teacher education context shows both a longer encounter with single supervisors (e.g., when a lesson is observed) and some professional activities that take place outside any observation (e.g., preparation for lessons, developing assignments, assessing students' work).

## Component 2: Task Model – Information Sources to Provide Evidence for Entrustability

The task model regarding relevant information sources at the workplace that provide evidence for a trainee's EPAs and Core Activities was developed. Those aim to serve the purpose of feedback to trainees and support for entrustment or proficiency decisions. Based on literature reviews and research among experts and stakeholders (Ten Cate et al. 2015; Leijen et al. 2017), the project shows that the most relevant information sources for trainees' progression in workplaces can be grouped into prior credentials, knowledge and skills tests in workplace settings, short practice observations, longitudinal practice observations, case-based discussion, product evaluation, self-report, and post hoc result checks. The EPA approach and the way of finding correct information sources are both described in a feasible guide (see Ten Cate et al. (2015)).

---

## Component 3: Evidence Model – Development of a Student Model-Driven Probabilistic Approach

Third, the developed EPAs and selected information sources, combined with technical considerations such as scalability, formed the input for the development of student models based on a probabilistic approach (Van der Schaaf et al. 2017). Decisions on entrustability or proficiency levels for activities were made on the basis of a set of workplace-based assessments, including written narrative information, e.g., written feedback by a supervisor. The underlying student model module advises on the following criteria:

1. Estimation of entrustability: What is currently the most likely level of entrustability or proficiency for this trainee, given the information in the portfolio? The answer to this question can be provided in terms of a probability distribution regarding the levels of that EPA or Core Activity given the current evidence:

$$P(\text{level } x \text{ for EPA} \mid \text{current evidence in portfolio})$$

2. Selection of improvement feedback: What feedback should be selected to give to the trainee, given his EPA or task level?
3. Selection of topic of interest: What EPA or Core Activity is at the moment the most of interest for a trainee and supervisor?

The UnBBayes library and the OpeNER Natural Language Processing toolkit were used for this purpose. A Multi-entity Bayesian Network approach (MEBN) (Laskey 2008) allowed building flexible student models that learn from incoming evidence. These models can be individualized but at the same time can be dealt with on a large scale with many concurrent trainees using the online environment. The MEBNs include five modules, namely, the:

- (a) Evidence collector: this interprets the individual pieces of (possible written) evidence or information about a trainee and translates it into more abstract and general terms.
- (b) Core student model: translates the portfolio and assessment data into the progress state of the trainee.
- (c) Context modeler: this describes the actual context for a given trainee, including models for the actual supervisors, assessors, and peers.
- (d) Feedback producer: this module must decide on whether feedback is required and, if yes, which feedback.
- (e) Aggregator: this part should be able to produce numerical data that can be visualized, together with data directly derived from the portfolio database.

These different parts of the student model have to work in close cooperation. They all consist of logical and probabilistic rules. The evidence collector consists of rules that decide, for instance, to translate written feedback that contains words like “excellent” and “well done” into the observation that “this feedback was positive with 80% of chance.” The context modeler uses the context information from the portfolio (e.g., information about the workplace, the supervisors, the tasks) and translates it into an observation such as “the assessment was done in a difficult setting with 60% of chance.” The core student model translates above statements and additional information from the portfolio into statements such as “this trainee is probably (>70%) at the highest entrustability level for this EPA.” The feedback producer takes output from the core model, the feedback, and input from the user to produce a statement like “it is probably wise (chance of 90%) to point the trainee at this moment to his lacking procedural skills in this EPA.” Such a statement would then result in a message to the user, for instance, visualized in a graph. The last part of the model, the aggregator, consists of the probabilistic knowledge in all other parts of the model, combined with aggregated data from the ePortfolio system. It might contain rules on how to select the best data to represent for a given situation.

Before a student model can be developed, different questions have to be answered among the users. Examples of questions are: When does a trainee require feedback? How do trainees perceive feedback? What kind of diagnoses are used by a supervisor to determine that a trainee requires feedback and what type of information sources are useful to make entrustment decision about critical responsibilities for trainees? Trainee’s motivation, self-regulation, and previous assessments are important in this regard. What timing of feedback is useful?

---

#### **Component 4: Presentation Model – Development of Written and Visual Feedback**

The presentation model addresses the written and visual feedback to be provided to trainees as well as their supervisors. Again, taking the requirements and specification as a starting point, this phase will develop the just-in-time feedback and visualization modules ready for integration into the ePortfolio system. In the project, Bayesian



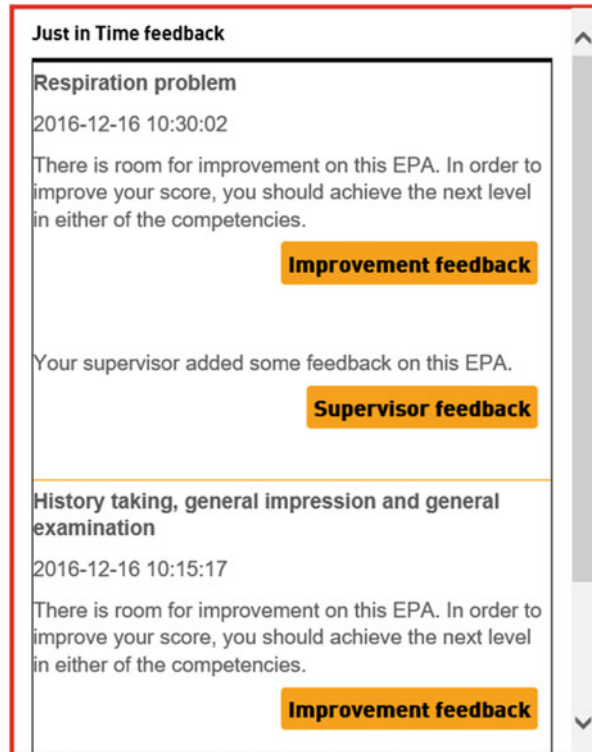
student models that are probabilistic in nature translate incoming ePortfolio data to represent progress states of the trainee in order to provide the most relevant feedback message to the trainee at any given moment. More specifically, the ePortfolio environment is enhanced with a Bayesian student model software module to monitor trainees' development on professional tasks, including a feedback module that delivers quantitative and written personalized feedback (denoted as "just-in-time" feedback, or JIT) and a visualization module that visualizes the feedback in terms of progress in the display (denoted as "visualization" or VIZ) (Van der Schaaf et al. 2017). The development of a feedback and visualization module demands input from the users on at least the following questions: What is feedback according to the users? What would trainees and supervisors like to see in the progress of learning of a trainee on the short and on the long term? What kind of feedback do they prefer, with what graphically display? With what frequency is feedback typically given and received? What are the time constraints for giving and receiving feedback? Where does the activity that must be assessed take place? Where is assessment performed? What kinds of devices are available when assessment is performed and received?

## Written Feedback

The developed system has a written feedback option that gives written personalized feedback to users. Besides the fact that supervisors or peers can write feedback in a trainee's portfolio, the project experimented with a natural language processor (NLP) that automatically identified and produced feedback messages to trainees or their supervisors based on incoming data. NLP tools aim to automatically interpret human language and their availability increased since the mid-1990s (Jarafsky and Martin 2008; McNamara et al. 2017). Based on the estimated performance scores in trainees' portfolios, *improvement feedback messages* are defined based on the rubrics that are underlying the system. For instance, when an estimated score of a trainee is near to entrustable level 2, the trainee will automatically get advice of actions that he or she can take to develop to level 3. This also counts for the other levels. The automatic feedback is defined beforehand by teams of domain experts that described many suggestions for what trainees can do to develop to a next level.

The student model module is used to decide which, if any, of the available improvement feedback messages should be selected from the underlying rubric for presentation to the trainee. The maximum probability is selected by the student model module for each EPA or Core Activity, and the trainee is given one improvement strategy for each plus supervisor feedback, if the supervisor gave any. See Fig. 1 for an example. The written feedback section on the dashboard in the ePortfolio environment is useful as it shows the available feedback of the most recent EPAs and Core Activities, aggregated in one overview. The trainee can quickly see what needs attention, and there is no need to scroll through the whole portfolio to get these insights.

**Fig. 1** Example of JIT feedback, regarding supervisor and improvement feedback displayed on the dashboard in a trainee's ePortfolio



Supervisors receive alerts, displayed as text messages. For each trainee who has at least one alert triggered, a button to navigate to his or her portfolio is available. Supervisors will see a list of trainees to whom they ought to pay special attention. From this, the supervisor can go to a trainee's portfolio to understand in detail the reasons behind the JIT message. Figure 2 shows an example.

## Visual Feedback

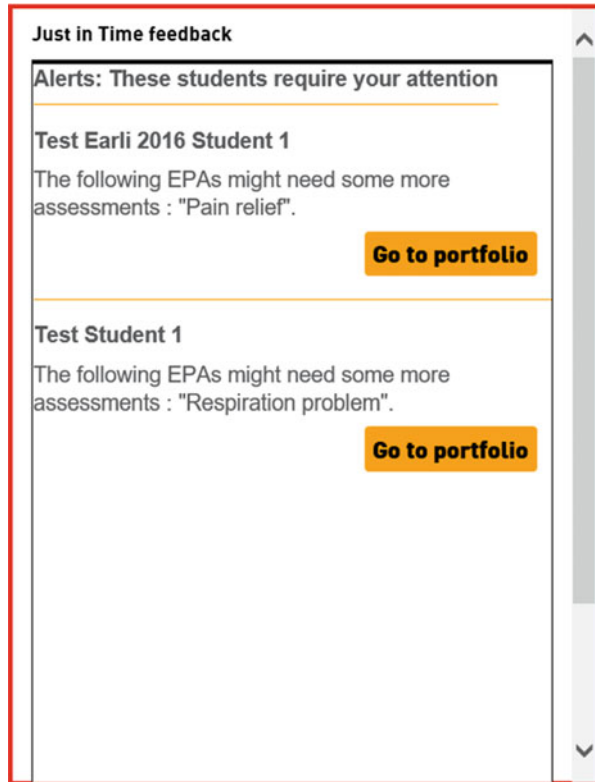
Trainees' progress is visualized in several ways, based on stakeholders' wishes in the project. Below some examples are shown.

*Timeline.* The timeline visualization provides an overview of a trainee's time-based development, using assessment forms as benchmarks (Fig. 3). It is interesting for users to track their development over time as they improve.

The dots in the timeline display the actual score for a trainee at a certain EPA or Core Activity. Inside the visualization, the user can:

- Hover on an assessment dot to see a summary of the assessment form in a pop-up box.
- Click on an assessment dot to see a written message from the assessment of that EPA or Core Activity in a pop-up box.

**Fig. 2** Example of written alerts to supervisors



- Go to a particular assessment form by clicking on the relevant button inside the pop-up box.
- Click on an EPA or Core Activity or on the legend explanation below to navigate to a timeline view of his or her development.
- Zoom in and out to see a longer or shorter period of time in the timeline, or use the dropdown list of preset time periods.
- A text analysis system that handles supervisor's written feedback, by recognition of positive, neutral, or negative elements and feedback this back "automatically" to trainees (see Fig. 4).

*Current performance.* The current performance visualization aimed to give the trainee an idea of where they are right now on their EPAs or Core Activities. It used the most recent scores for each EPA or Core Activity to show the user a contemporary picture of their performance. Current performance consists of two different visualizations presenting the same data: the spider diagram and the bar chart (see Fig. 5).

*Supervisor view.* Supervisors often supervise several trainees at a time. They will therefore benefit from an easy overview informing them, which trainees require attention. In order to fulfill this need, the project developed a specific



Fig. 3 Example of a timeline visualization

supervisor view in the shape of a timeline. The supervisor view comprises development curves for all the supervisor’s trainees in a single timeline visualization. In this visualization, a supervisor sees a timeline with graphs for each of their trainees. The graphs are generated by aggregating the trainees’ scores on different EPAs or Core Activities over time. This illustrates for the supervisor the approximated performance of each trainee (see Fig. 6).

### Component 5: Evaluation

The context of the evaluation concerned internships that trainees in the professions of medical, veterinary, and teacher education had to fulfill during a few weeks. It was assumed that ePortfolios enhanced with learning analytics functionalities contribute to motivation and feedback perception of trainees, because feedback can be provided more timely and personalized. A quasi-experimental study among 217 trainees of 4 institutes for professional education in 2 countries (the Netherlands and Estonia) was conducted to find out whether the ePortfolio with learning analytics impacted positively on trainees’ motivation for their internship, their assessment experience, and their use of the ePortfolio system. Data was collected at one institute for medical

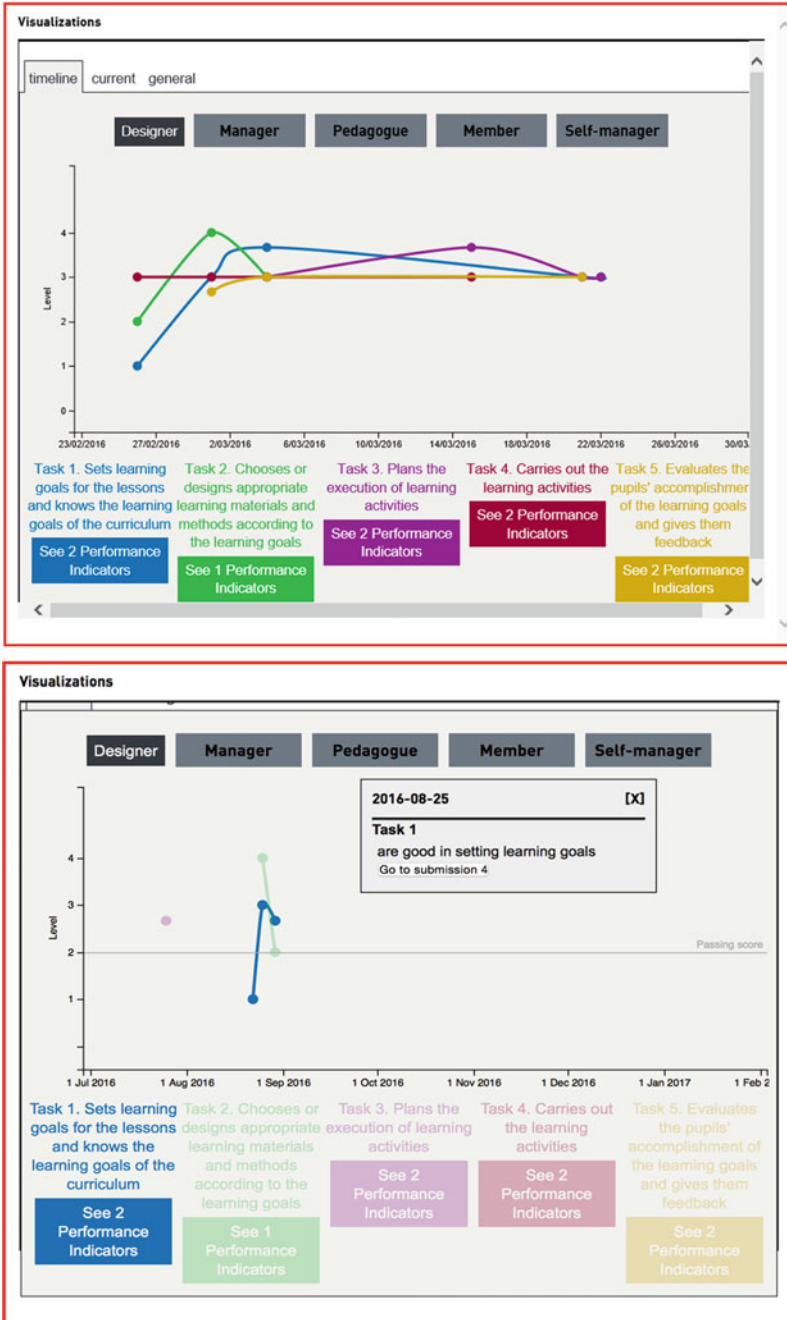


Fig. 4 Timeline with written feedback

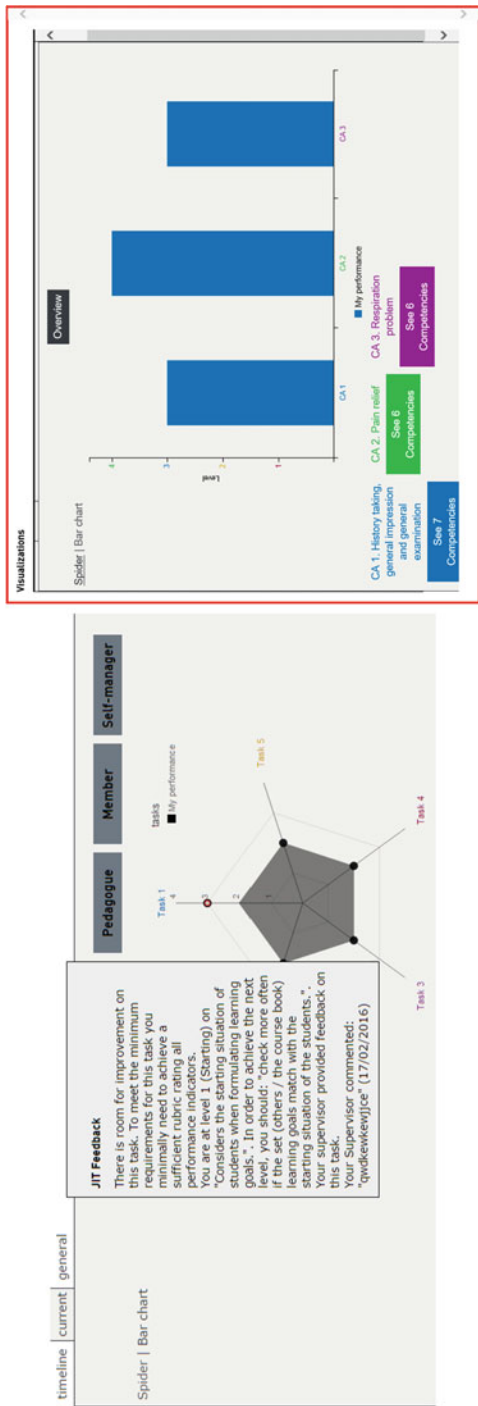


Fig. 5 Interaction with the spider diagram (left panel) or bar chart (right panel) reveals written feedback

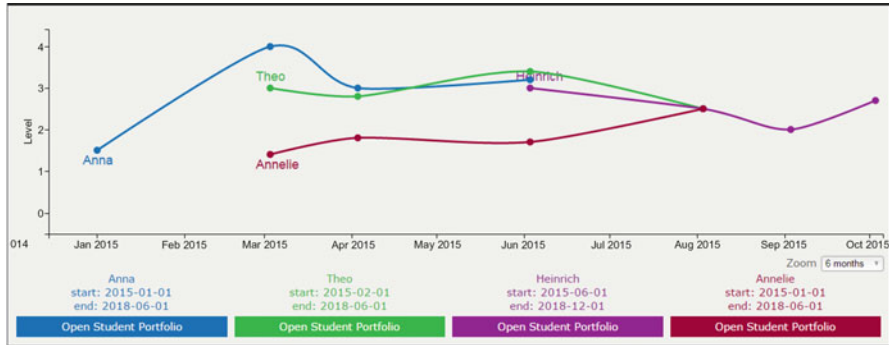


Fig. 6 Supervisor view

Table 1 Trainees’ use of written feedback (JIT) and visualizations (VIZ)

	n trainees that used the feature	Total n mouse clicks	Total time spent (minutes)
JIT, written feedback: improvement feedback, supervisor feedback	47	62	2037
VIZ, visualizations: timeline, performance, bar and spider chart	147	1949	8984

education (Utrecht, the Netherlands  $n = 56$ ), one institute from veterinary education (Utrecht, the Netherlands,  $n = 34$ ), and two institutes from teacher education (Utrecht, the Netherlands,  $n = 66$ ; Tartu, Estonia,  $n = 61$ ). Data was collected by questionnaires as well as by analyses of logs, i.e., amount of mouse clicks and time spent on written feedback (JIT) and visualization (VIZ) features in the ePortfolio environment. The questionnaires measured aspects of motivation (Ryan and Deci 2000) and assessment experience (Gibbs and Simpson 2003). Log files of trainees’ “mouse clicks” and time spent on the feedback features as presented in the former section were gathered to get insight into trainees’ use of the ePortfolio (Agudo-Peregrina Iglesias-Pradas conde-González and Hernández-García 2014).

Regarding trainees’ *motivation* for their internship, it turned out that trainees’ scores in the motivation questionnaire were rather high (at average around 3.5 on a 5-point scale) and that there were no differences between groups, indicating that their basic needs are mostly satisfied. This was also counted for trainees’ *assessment experience*.

In total mouse clicks and time spent on features were registered from 201 trainees (61 medical, 45 veterinary, 95 teacher education). Although the feature *timeline* had high numbers of visits and clicks, this did not count for the bar chart and spider chart. Almost none of the students clicked on this feature (Table 1).

In general, the students did not *use* the learning analytics modules as much as expected, or even if these features were used, students did not spend much time on looking at the represented content. Comparing the use of the two learning analytics

applications, i.e., the JIT with written feedback and the VIZ with visualizations, it can be concluded that the automated feedback module was used much less than the visualization module. The main benefit of the visualizations according to the respondents was that the VIZ module was easier to understand and it provided a simpler overview of the process the trainees made over time.

The results show that the learning analytics modules in the ePortfolio environment were not used as much as expected and that written feedback (JIT) was used less than the visualizations (VIZ).

---

## Conclusion

This chapter described a project that aimed to improve the quality of workplace-based feedback and assessment for trainees and supervisors through enhancing an existing ePortfolio environment with learning analytics. The ePortfolio collects and stores data about trainees' progress from diverse sources. Based on state-of-the-art probabilistic reasoning techniques, student models were created that allowed for aggregation and tailored just-in-time feedback. The learning analytics process as described in this chapter includes related processes (Elias 2011; Mislevy Behrens Dicerbo and Levy 2012; Toulmin 2003). First the domains with entrustable professional activities were defined. Then data were selected and captured. Next data were aggregated, and information was reported to make analyses, evaluations, and predictions based on the data. The human factor in learning analytics is represented by the trainees, content specialists, educational specialists, and technologists at workplaces throughout Europe.

The evaluation cycle, related to argumentation theory and evidence-centered design, provides useful insights into benefits and challenges of implementing ePortfolios enhanced with learning analytics in workplace-related contexts. Although the written feedback from the supervisors was highly valued, trainees did not or almost not use the automated feedback module. The visualization model, especially the feature "timeline," was used most by trainees. The main benefit of the visualization module according to the trainees was that it generated a simple overview of their development over time and was easy to understand.

There are, however, several scientific challenges that have to be dealt with. Firstly, the use of learning analytics for workplace-based feedback and assessments demands new solutions to make use of symbolic and numerical data and soft, written data and feedback as input to the models. This will require the use of text mining techniques and natural language processing to analyze written elements in order to resolve and encode them into probabilistic propositions to inform the student models. Examples of techniques that might be considered are the well-known latent semantic analysis but also more recent developments such as the application of ontologies or the application of sentiment analysis.

Foreseen practical challenges include the tailoring to trainees' and supervisors' feedback and assessment needs. Connecting learning analytics to ePortfolios demands multi-sorted learning and assessment tools at the work environment to be



used as an input into the system and a module for automated feedback provision. The overarching environment is assumed to improve the quality (validity and reliability) and efficiency of supervisors' and trainees' (self and peer) feedback and assessment at the workplace. However, this will only succeed when the environment is developed and implemented through the eyes of the users. This especially counts for the visualization dashboards for trainees and supervisors that will be developed to present the information at the workplace in a graphically easy to interpret way. First, this demands a strong integration of ePortfolios in the learners' curriculum as a tool for reflection, dialogues, and feedback on professional development. Second, training for trainees and supervisors to learn to work with the ePortfolio environment is fundamental.

Other practical challenges include the search for ways to easily integrate ePortfolios with other information systems. Since trainees alternately work in several organizations and bring their electronic portfolio with them, learning analytics-based electronic portfolios as used and improved in the described project in this chapter can enhance collaboration between trainees, supervisors, and organizations, for instance, by the exchange of information about trainees' development in organizations, and hence increase the learning opportunities for trainees. Here it is important to ensure that the use of data is aligned with the ethics of the institute or professional domain. Although it is common that the learner is the "owner" of the ePortfolio data and has to grant access to others (e.g., peers, supervisors) to enter the ePortfolios (e.g., in order to provide feedback), there is still the issue of datasets that are stored at servers and are limited in their transport (Greller and Drachler 2012; Selwyn 2015).

All in all it can be concluded that the use of learning analytics in ePortfolios is promising, but still in its infancy. Potentially it can contribute to more personalized, timely, and effective feedback at the workplace. In this end it contributes to the ultimate goal of learning at the workplace: entrusting professionals with, for instance, the critical care of patients, animals, and students.

**Acknowledgment** This study was conducted within the framework of the "Workplace-Based e-Assessment Technology for competency-Based Higher Multi-Professional Education" (WATCHME) project, supported by the European Commission 7th Framework Programme (grant agreement No. 619349). We thank all participants and members of the WATCHME project for their contributions: Charité Universitätsmedizin Berlin, Germany; Jayway, Denmark; Maastricht University, the Netherlands; Mateum BV., the Netherlands; NetRom Software SRL, Romania; Tartu Ülikool, Estonia; University of California San Francisco, USA; University Medical Center Utrecht, the Netherlands; University of Reading, UK; University of Veterinary Medicine, Hungary; and Utrecht University, the Netherlands.

---

## References

- Agudo-Peregrina A, Iglesias-Pradas S, Conde-González MA, Hernández-García A (2014) Can we predict success from log data in VLEs? Classification of interactions for learning analytics and their relation with performance in VLE-supported F2F and online learning. *Comput Hum Behav* 31:542–550. <https://doi.org/10.1016/j.chb.2013.05.031>

- Barbera E (2009) Mutual feedback in e-portfolio assessment: an approach to the netfolio system. *Br J Educ Technol* 40(2):342–357. <https://doi.org/10.1111/j.1467-8535.2007.00803.x>
- Barrett HC (1998) Strategic questions: what to consider when planning for electronic portfolios. *Learn Lead Technol* 26:6–13
- Billett S (2004) Workplace participatory practices: conceptualising workplaces as learning environments. *J Work Learn* 16(6):312–324. <https://doi.org/10.1108/13665620410550295>
- Bryant LH, Chittum JR (2013) ePortfolio effectiveness: a(n ill-fated) search for empirical support. *Int J ePortfolio* 3(2):189–198
- Butler P (2006) A review of the literature on portfolios and electronic portfolios. Massey University College of Education, Palmerston North
- Dekker-Groen A, Van der Schaaf M, Stokking K (2012) Performance standards for teachers supporting nursing students' reflection skills development. *J Nurs Educ Pract* 2(1):9–19. <https://doi.org/10.5430/jnep.vn1p9>
- Doyle GJ, Garrett B, Currie LM (2014) Integrating mobile devices into nursing curricula: opportunities for implementation using Rogers' diffusion of innovation model. *Nurse Educ Today* 34(5):775–782. <https://doi.org/10.1016/j.nedt.2013.10.021>
- Duijn CC, Welink LS, Mandoki M, ten Cate OT, Kremer WD, Bok HG (2017) Am I ready for it? Students' perceptions of meaningful feedback on entrustable professional activities. *Perspect Med Educ* 6:256. <https://doi.org/10.1007/s40037-017-0361-1>
- Dysthe O, Engelsens KS (2011) Portfolio practices in higher education in Norway in an international perspective: macro-, meso- and micro-level influences. *Assess Eval High Educ* 36(1):63–79. <https://doi.org/10.1080/02602930903197891>
- Elias T (2011) Learning analytics: definitions, processes and potential. Creative Commons Attribution 3.0
- Ericsson A, Pool R (2016) *Peak: secrets from the new science of expertise*. Harcourt, Houghton Mifflin
- Ericsson KA, Charness N, Feltovich PJ, Hoffman RR (eds) (2006) *The Cambridge handbook of expertise and expert performance*. Cambridge University Press, New York
- Eynon B, Gambino LM, Török J (2014) What difference can ePortfolio make? A field report from the connect to learning project. *Int J ePortfolio* 4(1):95–114
- Feltovich PJ, Prietula MJ, Ericsson KA (2006) Studies of expertise from psychological perspectives. In: Ericsson KA, Charness N, Feltovich P, Hoffman RR (eds) *Cambridge handbook of expertise and expert performance*. Cambridge University Press, Cambridge, pp 41–67
- Frank JR (2005) *The CanMEDS 2005 physician competency framework. Better standards, better physicians. Better care*. Ottawa, The Royal College of Physicians and Surgeons of Canada
- Gibbs G, Simpson C (2003) Measuring the response of students to assessment: the assessment experience questionnaire. In: *11th Improving Student Learning Symposium*, pp 1–12
- Greller W, Drachsler H (2012) Translating learning into numbers: a generic framework for learning analytics. *J Educ Technol Soc* 15(3):42–57
- Grossman P, Hammerness K, McDonald M (2009) Redefining teaching, re-imagining teacher education. *Teach Teach Theory Pract* 15(2):273–289. <https://doi.org/10.1080/13540600902875340>
- Hamp-Lyons L, Condon W (2000) *Assessing the portfolio: principles for practice, theory, and research*. Hampton Press, Cresskill
- Hattie J, Timperley H (2007) The power of feedback. *Rev Educ Res* 77(1):81–112. <https://doi.org/10.3102/003465430298487>
- Jafari A, Kaufman C (eds) (2006) *Handbook of research on eportfolios*. IDEA Group Publishing, Hershey
- Jarafsky D, Martin JH (2008) *Speech and language processing: an introduction to natural language processing, computational linguistics and speech recognition*, 2nd edn. Prentice Hall, Upper Saddle River
- Jonker G, Hoff RG, Ten Cate O (2015) A case for competency-based anaesthesiology training with entrustable professional activities: an agenda for development and research. *Eur J Anaesthesiol (EJA)* 32(2):71–76. <https://doi.org/10.1097/EJA.000000000000109>
- Kane MT (1992) An argument-based approach to validity. *Psychol Bull* 112(3):527

- Kennelly E, Osborn D, Reardon R, Shetty B (2016) Guidance for ePortfolio researchers: a case study with implications for the ePortfolio domain. *Int J ePortfolio* 6(2):117–125. <http://www.theijep.com>
- Kovanović V, Joksimović S, Gašević D, Hatala M, Siemens G (2015) Content analytics: the definition, scope, and an overview of published research. In: *Handbook of learning analytics*. SoLAR, Edmonton. <https://doi.org/10.18608/hla17.007>
- Laskey KB (2008) MEBN: a language for first-order Bayesian knowledge bases. *Artif Intell* 172(2–3):140–178. <https://doi.org/10.1016/j.artint.2007.09.006>
- Leijen A, Slob B, Malva L, Hunt P, van Tartwijk JWF, van der Schaaf MF (2017) Performance-based competency requirements for learner teachers and how to assess them. *Int J Inf Educ Technol* 7(3):190–194. <https://doi.org/10.18178/ijiet.2017.7.3.864>
- McNamara DS, Allen LK, Crossley SA, Dascula M, Perret CA (2017) Natural language processing and learning analytics. In: Lang C, Siemens G, Wise A, Gašević D (eds) *Handbook of learning analytics*. SoLAR, Edmonton, pp 93–104. <https://doi.org/10.18608/hla17.008>
- Mislevy RJ, Behrens JT, Dicerbo KE, Levy R (2012) Design and discovery in educational assessment: evidence-centered design, psychometrics, and educational data mining. *JEDM-J Educ Data Min* 4(1):11–48
- Mulder M (2014) Conceptions of professional competence. In: Billett S, Harteis C, Gruber H (eds) *International handbook of research in professional and practice-based learning*. Springer, Dordrecht, pp 107–137
- Peacock S, Murray S, Scott A, Kelly J (2011) The transformative role of ePortfolios: feedback in healthcare learning. *Int J ePortfolio* 1(1):33–48. <http://www.theijep.com>
- Rezgui K, Mhiri H, Ghédia K (2014) Ontology-based e-Portfolio modeling for supporting lifelong competency assessment and development. *Procedia Comput Sci* 112:397–406. <https://doi.org/10.1016/j.pro.2017.08.041>
- Royal College of Veterinary Surgeons (RCVS) (2014) Practice standards scheme manual. Royal College of Veterinary Surgeons, London
- Ryan RM, Deci EL (2000) Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *Am Psychol* 55(1):68. <https://doi.org/10.1037/110003-066X.55.1.68>
- Sadler DR (2010) Beyond feedback: developing student capability in complex appraisal. *Assess Eval High Educ* 35(5):535–550. <https://doi.org/10.1080/02602930903541015>
- Selwyn N (2015) Data entry: towards the critical study of digital data and education. *Learn Media Technol* 40(1):64–82. <https://doi.org/10.1080/17439884.2014.921628>
- Siemens G, Gašević D (2012) Guest editorial – learning and knowledge analytics. *Educ Technol Soc* 15(3):1–2
- Ten Cate O (2005) Entrustability of professional activities and competency-based training. *Med Educ* 39:1176–1177
- Ten Cate O, Chen HC, Hoff RG, Peters H, Bok H, Van der Schaaf M (2015) Curriculum development for the workplace using entrustable professional activities (EPAs): AMEE guide no 99. *Med Teach* 37(11):983–1002
- Toulmin SE (2003) *The uses of argument*. Updated edition. Cambridge University Press, Cambridge, UK
- Van der Schaaf MF, Stokking K, Verloop N (2008) Developing and validating a design for teacher portfolio assessment. *Assess Eval High Educ* 33(3):245–262. <https://doi.org/10.1080/02602930701292522>
- Van der Schaaf M, Baartman L, Prins F (2012) Exploring the role of assessment criteria during teachers' collaborative judgement processes of students' portfolios. *Assess Eval High Educ* 37(7):847–860
- van der Schaaf M, Donkers J, Slob B, Moonen-van Loon J, van Tartwijk J, Driessen E, ... Ten Cate O (2017) Improving workplace-based assessment and feedback by an E-portfolio enhanced with learning analytics. *Educ Technol Res Dev* 65(2):359–380. <https://doi.org/10.1007/s11423-016-9496-8>
- Van Schaik S, Plant J, O'sullivan P (2013) Promoting self-directed learning through portfolios in undergraduate medical education: the mentors' perspective. *Med Teach* 35(2):139–144

- 
- Warren SJ, Lee J, Najmi A (2014) The impact of technology and theory on instructional design since 2000. In: Spector JM, Merrill MD, Elen J, Bishop MJ (eds) Handbook of research on educational communications and technology, 4th edn. Springer, New York, pp 89–99
- Wisman-Zwarter N, Van der Schaaf M, Ten Cate OT, Jonker G, Van Klei WA, Hoff R (2016) Defining the content of Anaesthesiology training with entrustable professional activities. A delphi study. *Eur J Anesthesiol* 33(8):559–567