LiftUpp: Support to develop learner performance

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Abstract. Various motivations exist to move away from the simple assessment of knowledge towards the more complex assessment and development of competence. However, to accommodate such a change, high demands are put on the supporting e-infrastructure in terms of intelligently collecting and analysing data. In this paper, we discuss these challenges and how they are being addressed by LiftUpp, a system that is now used in 70% of UK dental schools, and is finding wider applications in physiotherapy, medicine and veterinary science. We describe how data is collected for workplace-based development in dentistry using a dedicated iPad app, which enables an integrated approach to linking and assessing work flows, skills and learning outcomes. Furthermore, we detail how the various forms of collected data can be fused, visualized and integrated with conventional forms of assessment. This enables curriculum integration, improved real-time student feedback, support for administration, and informed instructional planning. Together these facets contribute to better support for the development of learners' competence in situated learning setting, as well as an improved experience. Finally, we discuss several directions for future research on intelligent teaching systems that are afforded by using the design present within LiftUpp.

1 Introduction

It is widely accepted that improved employability and salary prospects are key drivers for undertaking higher education. Ensuring employability requires that universities develop 'highly skilled graduates who are able to respond to the ever changing and complex needs of the contemporary workplace' [2]. The importance of this link between university education and employability is championed by the UK government, with employment as one of the key evaluation metrics for the Teaching Excellence Framework [8], which also stresses the importance of 'Stretch' (standards and assessment being effective in stretching students to develop independence), and 'Personalised Learning' (students' academic experiences being tailored to the individual, maximising rates of retention, attainment and progression). Unfortunately, traditional approaches to university education are focused on students gaining and demonstrating knowledge, and often little emphasis is placed on its contextual application to the real-world.

An exception is within medical programmes, especially in dentistry, where the regulating bodies, such as the General Dental Council (GDC) in the UK, require all graduates to be appropriately competent at the point of graduation [9]. In this context, competency refers to the 'ability (of the learner) to adapt and to flexibly apply and develop knowledge and skills in the face of evolving circumstances' [10] across multiple domains (Professionalism, Management & Leadership, Knowledge, Communication, Clinical). However, to support the development of competency, new and sophisticated methods of assessment that are seamlessly integrated with curriculum design are required.

This need for increased sophistication and integration puts high demands on the e-infrastructure because it requires more intelligent systems that can be used in the work place every day, and that can fuse all forms of assessment data together. These systems must also be able to enhance student development through personalised real time feedback to drive changes to learner self-regulation. Moreover, the information these systems provide must be robust and defensible to enable safe decisions on student progress in dentistry education in order to protect the public [7].

In this paper, we describe LiftUpp, a system developed at the School of Dentistry at the University of Liverpool, which has been specifically designed to meet these demanding requirements. Therefore, LiftUpp offers the opportunity to spawn cutting edge approaches to Artificial Intelligence in Education (AIED), which can be applied to all (including clinical) subjects.

2 Background and Related Work

Over the last decades, in dentistry, as well as other fields of higher education, more focus has been put on graduate employability. In terms of Miller's pyramid [14]—which divides learner competence into 4 levels of increasing mastery: *knows*, *knows how*, *shows how* and *does*—this means that a strong emphasis needs to be put on the higher levels of the hierarchy. Moreover, it is important to assess and stimulate the improvement of student *performance* over time:

> 'Competence indicates what people can do in a contextual vacuum, under perfect conditions. This might be evident using controlled assessment methods looking at the lower tiers of Millers pyramid. Performance, however, indicates how people behave in real life, on a day-to-day basis.' [12]

One school of thought is that a critical pedagogy for developing performance in students is *deliberate practice*: learners are systematically challenged by selecting tasks of increasing difficulty, particularly targeting those aspects that the learner needs to improve. This requires high quality multisource feedback (in dentistry education, for example, from both staff and patients [7]). In other words, in moving towards educational systems that focus on employability, it is needed to (1) have accurate skill or *performance* assessment, (2) identify the best tasks to stimulate learning, (which depends on assessment as well as on models of student learning), (3) provide the right feedback at the right times.

We believe that this presents a huge opportunity for applying techniques from the field of Artificial Intelligence in education (AIED). For instance, data-driven models of student learning and knowledge assessment [11, 13, 20] directly target need (1) and better ways of providing feedback [19] or hints [3] or adaptive selecting next assignments [16] fall squarely in research on *intelligent tutoring systems (ITSs).* The potential benefits of ITSs in more conventional teaching are clearly demonstrated by a number of systems, such as the Cognitive Tutor [17], which led to better student learning in a Algebra course.

However, in dentistry education a large part of the assessment is *workplace based*, i.e., consists of actual treatments that are (under supervision) performed on real patients. In particular, in the School of Dentistry at the University of Liverpool, students need to train to develop skills for a fixed, but large set of *procedures* (i.e., particular dental treatments). These procedures are trained for in clinical *sessions* (i.e., one training attempt for a particular procedure). These sessions are observed by *observers,* instructors that both assesses the performance and that step in when needed. The number of sessions that a student takes for a particular procedure is not fixed; they need to demonstrate that they can perform the procedure consistently well. Such workplace-based assessment settings are difficult to address with existing AIED techniques due to a few main reasons.

First, most existing techniques have been operationalised in much simpler settings, thus allowing the imposition of strong assumptions underlying the proposed methods. For instance, the Cognitive Tutor is based on the theory of ACT-R [1], which assumes that skills and knowledge can be decomposed into so-called *knowledge components (KCs)*, which can subsequently be tracked (frequently referred to as *knowledge tracing* [4]). Ritter et al. [17] were able to come up with a suitable decomposition of their algebra domain, but in workplace-based settings this might be much more difficult.

A second reason, and direct consequence of the first, is that, for most approaches, the data collection is more straightforward. For instance, the learner models examined by Rafferty et al. [16] are trained on sequences of data of the form {<exercise1, correct_answer1>, <explain_action>, <exercise2, incorrect_answer2>, ...}. Here, each observation in the sequence directly corresponds to a possible transition of the learners knowledge state (in case of an explain action) or a observation of it (in case of an exercise). Given that the definition of KCs is much more difficult in workplace based settings, the question of what data to collect (e.g., at what resolution) and how to collect it become difficult.

Third, educational programs with a workplace based component inherently lead to multi-source data, which can significantly complicate fusing the resulting data. Moreover, as we argued, the information that we want to infer should relate to predictions of performance over time, which is arguably more complex than just trying to predict the current state of a number of KCs in a learner.

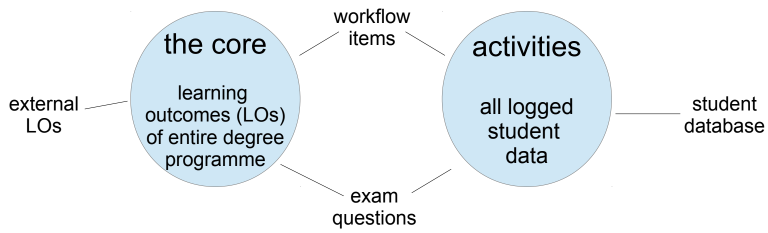


Fig. 1: A graphical overview of the Core of LiftUpp.

These complications present large challenges for the AIED community. In the remainder of this paper we present aspects of LiftUpp that make a first step in addressing some of these challenges. In particular, LiftUpp collects data on performed treatments in terms of what can be observed not what constitutes jumps in learner knowledge, thus bypassing the question of KC definition. It also operationalises this large-scale data collection problem in an effective way. As such, the system establishes an approach for data collection that can serve as a starting point for alternatives to knowledge tracing, such as the recently proposed variant of knowledge tracing based on deep learning [15], that are less dependent on particular properties of structured domains. LiftUpp also includes (preliminary) methods and metrics for assessing learner performance over time in workplace-based teaching. In these steps to address the above challenges lies the value of the system for the AIED community.

3 Overview of the LiftUpp Platform

LiftUpp is a digital educational platform designed to support quality-assured assessment, feedback, curriculum design and mapping. Its design is grounded in pedagogy and directly addresses the issues of complex data collection, triangulation and integration with stakeholder outcomes, as well as the provision of detailed feedback to drive changes to learner self-regulation through engendering the right educational impact, and it clears the way for applying AI and data-driven improvements to workplace-based education. It is the most sophisticated digital educational platform for workplace-based assessment used in dentistry, and is currently deployed in 70% (10 out of 14) of UK dental schools, as well as in veterinary medicine, physiotherapy, nursing and other healthcare courses.

An overview of the LiftUpp platform is given in Fig. 1. The figure shows the 'core', which contains the learning outcomes of the entire program (both internal as well as those of external stakeholders such as accreditation bodies), and connects them to exams, and, in fact, individual exam questions and *work flow items* (discussed further below), of treatments that the students need to perform. Sitting off the core are several modules, which currently comprise: an assessment building module (with support for exam setting, QA, blueprinting, psychometrics, reviewing, results, feedback); an iPad-based data collection module; and a web portal (system administration, data analysis, collation and display). Each of these modules is mapped to the core in a one to one or one to many relationship, which enables every item of collected data to be instantly mapped, blueprinted, and integrated to any stakeholder, any domain, and any metadata with which it is collected such as location, staff member, patient etc. For instance, Fig. 2 shows an example how the part of the curriculum can be investigated in the context of learning outcomes.

Outcome	WBA Coverage	Oral Diseases	Finals SBA (Year 5) - October 2016 - Formative
1 - Individual patient care	-	-	-
1.1 - Foundations of practice: The registrant will be able to apply to the practice of dentistry principles that derive from the biomedical, behavioural and materials sciences. The registrant will recognise and take account of the needs of different patient groups including children, adults, older people, and those with special care requirements throughout the patient care process.	-	-	-
1.1.1 - Explain, evaluate and apply the principles of an evidence-based approach to learning, clinical and professional practice and decision making	YES	NO	199, 2683, 3624, 3652
1.1.2 - Critically appraise approaches to dental research and integrate with patient care	YES	NO	
1.1.3 - Identify oral diseases and explain their relevance to prevention, diagnosis and treatment	YES	YES	3, 7, 9, 35, 40, 43, 44, 56, 63, 64, 80, 81, 121, 130, 131, 144, 176, 199, 207, 210, 245, 257, 293, 298, 346, 368, 391, 467, 485, 488, 498, 501, 552, 557, 566, 572, 597, 606, 619, 651, 691, 838, 840, 848, 855, 856, 862, 865, 888, 892, 906, 907, 913, 918, 919, 952, 954, 966, 1321, 1355, 1450, 1469, 1503, 1528, 1533, 1534, 1536, 1604, 1609, 1623, 1639, 1650, 1651, 1654, 1655, 1686, 1720, 1721, 1724, 1792, 1794, 1799, 1826, 1927, 2073, 2139, 2431, 2596, 2649, 2675, 2683, 2690, 2856, 2938, 2998, 3022, 3067, 3069, 3072, 3113, 3280, 3307, 3317, 3354, 3534, 3610, 3611, 3612, 3622, 3624, 3634, 3639, 3652, 3655, 3686, 3707

Fig. 2: The mapping data returned when the system is asked 'show me the work-based (WBA) coverage, Oral diseases teaching, and questions used in the final examination (Oct 2016) for each GDC learning outcome'.

This mapping of every single element of the entire degree program to the desired learning outcomes is what enables new forms of interpretation of the performance and competence of learners against the set of learning outcomes. We will discuss such novel forms of interpretations and resulting ways of supporting the development of learners in Section 5. First, however, we discuss the collection of data in Section 4.

4 Data Collection for Workplace-based Education

While storing assessment results of students is nothing novel in principle, a salient feature of LiftUpp is the level at which these are recorded, and their ability to be integrated together against each learning outcome. This opens the way for LiftUpp to be the first platform capable of full programmatic assessment, which is the ultimate expression of assessment for learning [18], where all assessments are deliberately designed and integrated to both develop and demonstrate each learning outcome in a student-centred manner. In the extreme, the importance of individual assessments themselves melt away and just supply data on learner performance with respect to the learning outcomes. In this paradigm, progression is based on performance stability and not on passing single tests, making it much better aligned to the needs of the real-world workplace [7].

However, to realise this, one significant challenge lies in effectively managing data components from multiple sources. For the use of LiftUpp in dentistry, this required the collection of daily observational data from 300 students in the

DI	Description
1	UNABLE to do this. Has caused harm or does not seek essential guidance.
2	UNABLE to do this independently at present. Largely demonstrated by tutor.
3	UNABLE to do this independently at present but able to complete, to the required quality, with significant help, either procedural or by instruction.
4	ABLE to do this partially independently at the required quality, but requires minor help with aspects of the skill, either procedural or through discussion.
5	ABLE to do this independently at the required quality. This may include confirmatory advice from the tutor where the student seeks appropriate assurance.
6	ABLE to meet the outcome independently, exceeding the required quality.

Fig. 3: The 6-point scale employed in LiftUpp.

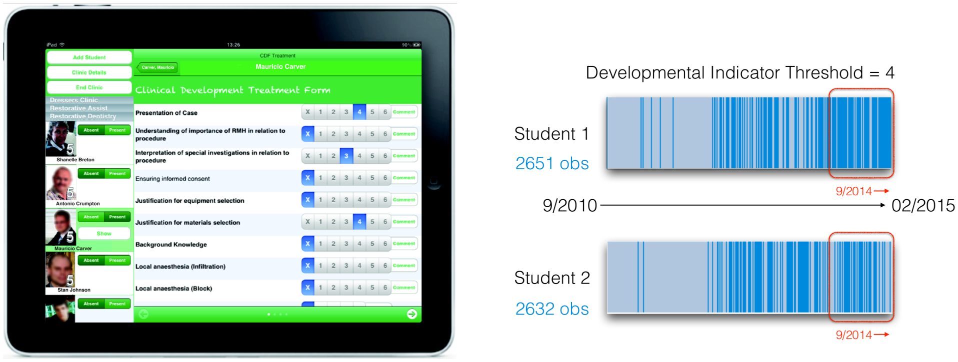
workplace in 20 different sites, from 100 different staff, spanning 165 learning outcomes, along with data from other forms of assessment. While this is challenging by itself, it is further complicated by the inherent difficulty of objectively assessing the quality of treatments performed by students.

Observations using Work Flows. To enable objective assessment, LiftUpp uses the combination of a 6-point scale and a work flow model of data collection. Within the 6-point scale, shown in Fig. 3, each point is known as a 'developmental indicator'. The scale is based on evidence that suggest objectivity is enhanced when scales are grounded in the developing the independence of the learner [5].

Data supports the validity and reliability of this scale [6]. The work flow model orders the required observations into a work flow order making it simple for the staff to observe the maximum amount of data in real time. A key feature of the approach is that is not an assessment, i.e., staff do not stand and watch everything and 'tick boxes'. The approach is one of observation and feedback, where staff only record what they see. Data suggest that the approach is both efficient and acceptable to staff, and the average member of staff is able to make 18 observations per session, per student (staff:student 1:8). This translates to the average student having 5061 observations from 52 different members of staff by the time of graduation.

Recording Performance. The above work flow based approach was initially rolled out using paper forms that were optically read. This was because, in 2009, mobile technology was not up to the task, and due to its real-time observational nature in the clinic desktop computers were considered as to be a barrier to the process. While this worked in principle, the amount of administrative overhead was huge. At the time 80,000 paper forms per year were being generated, which lead to around a 10% data loss, delays in data upload, and made it impossible for students to see any written comments that staff wished to provide to enhance their performance. In 2010, following the release of the iPad we could operationalise the process as intended.

The app, shown in Fig. 4a, is tailored to deal with all possible work flows and is designed for easy navigation during observations. For instance, it allows for



(a) iPad interface for judging a clinical session.

(b) *Barcodes* visualise consistency.

Fig. 4: Collection and visualization of data.

rapid switching between students, and the main part of the screen is designed to simultaneously display many of the workflow items. In addition, the app is aware of its location so the correct work flows can be automatically selected, the right students can be assigned in order to allow simple monitoring of their attendance, and the right staff can sign in, or make the system aware they are covering for a colleague. In addition, the app was designed to work-off line as Wi-Fi access is not constant in some clinical areas. At the end of the session each student is provided with personalised feedback on the device, and then signs out to confirm they have seen it, at which point their record is locked. Following the sign out of all students, the staff member signs out and the data it uploaded to the core.

5 Data Fusion, Visualization & Use

While we believe that advanced AI techniques have the potential to radically improve the development of performance in students, the current system already benefits from the collected data in various ways. Here, we review these, thus underlining how LiftUpp makes a first step towards data-supported improvement of dentistry and, more generally, workplace-based education.

Quality Assurance for Curriculum and Assessment Design. The fact that all exam questions and work flow items are coupled to learning outcomes, means that is it is possible to automatically verify if the requirements of accreditation bodies are satisfied. In fact, LiftUpp takes this one step further by providing an interface to semi-automatically generate exams meeting those requirements. In addition, the exam question database can also be used (e.g., by external examiners) to check the quality of the questions. Furthermore, the collected data from taken exams can be used to track the performance on individual questions, thus allowing for further improvements.

Progress Monitoring. One of the greatest challenges is to take the complex data and display it in a manner that is simple for both the learner and the staff to understand. With respect to the presentation of the clinical performance data the challenges are significant: How do you display 5061 data points from hundreds of clinical sessions, covering 30 skills, in a meaningful way? We have found that, without support, staff resort to 'counting' the numbers of procedures and problems. This is far too simplistic: we need to judge performance over time. Students should not only attain a level of performance, but also *consistently* perform at that level afterwords.

We have not fully resolved this problem, and work is ongoing, but a major step forwards was the definition of what we have termed 'sessional consistency': the fraction of a student's sessions that meets a desired performance threshold level. The logic to doing this is that undertaking the job of dentistry is complex, and each skill is interdependent. Therefore, in any area where any skill falls below the required level, the ability to do the job is affected. To represent this sessional consistency visually we developed the 'barcode' view. Fig. 4b shows two examples of barcodes. They display each observation that meets the required level of performance (in this case, it was assessed as 4 or higher) in blue. The top barcode conveys that the student has learned to perform consistently well over the last period of time, while the bottom barcode corresponds to a student that is able to reach the required level, but does not yet do so consistently. As more data becomes available, it will also be possible to have better expectations of the development in the early stages of studies, thus allowing for better early detection of problems and advice to students.

Adaptive Instructional Planning. The ability to better monitor student progress is also useful for creating adaptive schedules for students. The patients that require a particular treatment at any given time are a limited resource, and as such the allocation of students to patients is an important question in a dental school. The insight that LiftUpp provides about the students performance is used to decide which students will benefit most from additional practice opportunities, while other students are put in 'holding patterns', which means that the frequency of their workplace-based assessment is reduced or shifted towards less resource-limited treatments.

Feedback for Students. The bar codes are not only used for progress monitoring, but can also be seen by students, to inform their holistic development. The students can investigate their own performance in detail through the additional information provided: they can drill down to the level of each individual skill and see both the contextual performances and their experience. Additionally, the interface presents the student with a view of their 'portfolio', shown in Fig. 6a which gives insight in what procedures are sufficiently demonstrated and which need more training. This produces a meaningful transferable employability profile, able to inform employers over the individual learner's strengths and weakness, so ongoing graduate training can also be tailored.

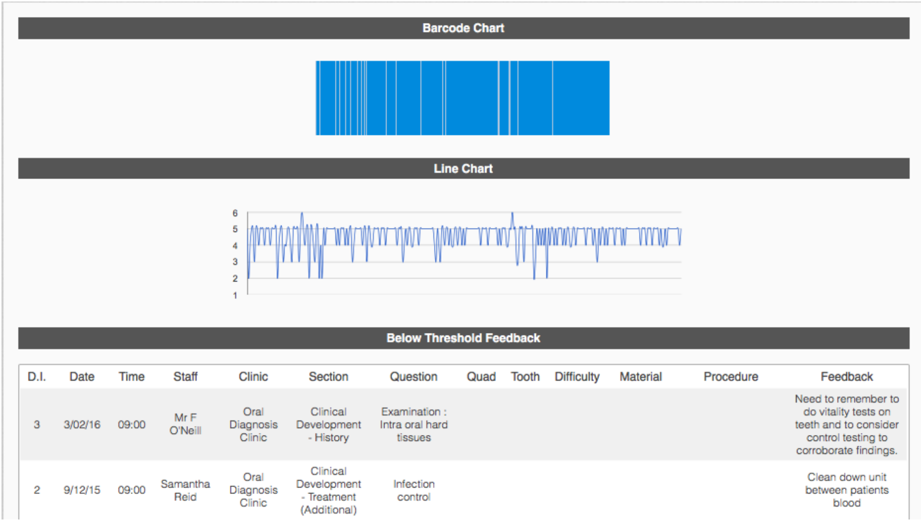


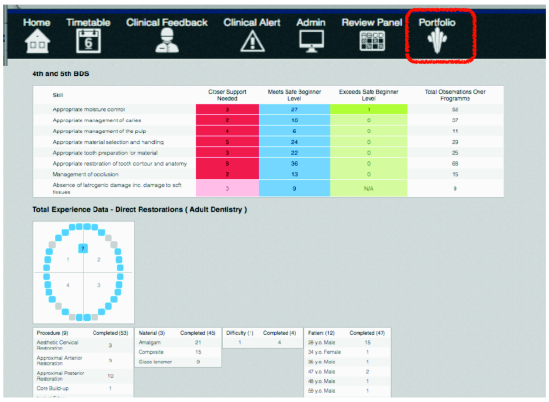
Fig. 5: Student feedback in LiftUpp.

Feedback for Observers. A further function that is allowed by the LiftUpp design is the ability to explore staff calibration, since the collected data can be sliced by member of staff. The proper use of the developmental indicators is essential for the credibility and trustworthiness of the data, but also requires training. Well-trained staff use the full range of the developmental indicator scale, but some staff may only use 2 or 3 out of 6 points on the scale. This means that their '3' may be equivalent to someone else's '2'. The LiftUpp can give staff members insight into indicators for which their assessment deviates from other members of staff, as illustrated in Fig. 6b. This information can be used to train observers.

Defensible Decisions at Board of Examiners. A final way in which LiftUpp currently uses the collected data is by supporting the decisions at the board of examiners. Defensibility in clinical programmes is a big issue because we are talking about ending someone's career before it even starts. The potential lifelong earnings of a dentist have been estimated to be £3.5M, and this is what the school could be sued for; a wrong decision over student progression can be catastrophic for the institution. The defensibility of any judgement is ultimately related to the quality of the data collected, and how it is interpreted, and on these fronts LiftUpp has significantly pushed the envelope.

6 Deployment and Effectiveness

LiftUpp is a system that is developed in a deployed context; it has been in use in the School of Dentistry at the University of Liverpoool since 2009, and has



(a) Feedback to students in the form of their portfolio.

Developmental Indicators

Staff Name	All Data	% 1	% 2	% 3	% 4	% 5	% 6
A	51	0	0	0	4	41	55
B	36	0	0	6	75	19	0
C	25	0	0	0	0	100	0
D	23	0	4	0	4	65	26
E	31	0	3	0	10	87	0
F	325	0	0	2	16	81	1
G	91	0	0	8	73	20	0
H	113	0	0	1	14	85	0
I	101	0	0	2	5	88	5
J	6	0	0	17	67	17	0
K	168	0	0	2	8	68	23

(b) Slicing over staff for feedback on assessment.

Fig. 6: Some other ways in which LiftUpp facilitates providing feedback.

made an unprecidented impact on the student experience, and their learning. This is perhaps most clearly expressed by the student satisfaction ratings (as measured by the national student satisfaction (NSS) survey), shown in Fig. 7. The figure clearly shows that there are improvements over all four categories, but that especially the satisfaction with respect to assessment & feedback as well as organization & management have markedly improved since the introduction of LiftUpp.

The breadth and quality of the collected data is high and has been key in running a more effective administration. We estimate that LiftUpp has saved approximately £150,000 in administration costs. Moreover, the data has been used successfully in several legal cases where students have challenged decisions, all the way to the Office of the Independent Adjudicator and General Dental Council.

This success has caused other dental schools to take interest and LiftUpp is now deployed in 70% of UK dental schools. Moreover, in recent years there has also been interest from other workplace-based disciplines, leading to deployments in veterinary medicine, physiotherapy, nursing and other healthcare courses.

7 Conclusions & Future Research Directions

In this paper, we presented some of the challenges addressed by LiftUpp for supporting the development of learners' performance in dentistry. The primary motivation for initiating the development for LiftUpp came from the need to comply with regulations and improve student satisfaction. However, in doing so, LiftUpp has to a large extent addressed the difficulties that one faces in terms of data collection when trying to apply data-driven approaches as developed in the AIED community to educational programs based on workplace based

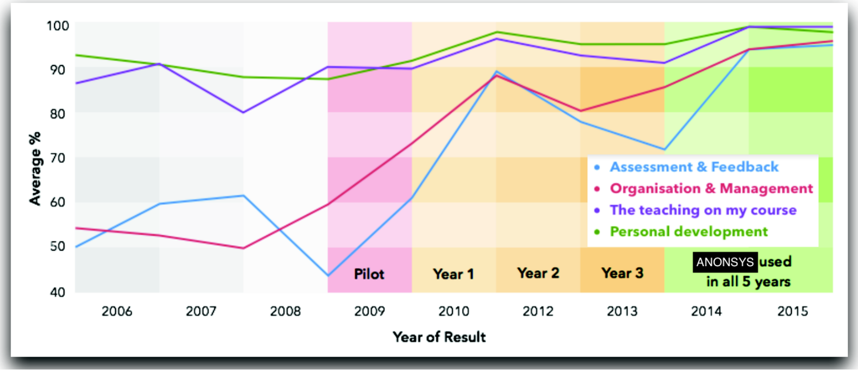


Fig. 7: Student satisfaction ratings since the introduction of LiftUpp.

assessment. In addition, LiftUpp makes some first but effective steps in dealing with the resulting data fusion problem for a variety of uses ranging from quality assurence, to various forms of feedback and instructional planning. Moreover, the years in which the system has been employed has now generated a wealth of data that may serve as the basis for better data fusion techniques and thus form the basis of many future directions of research. The three most promising directions we describe in the remainder of this section.

Advanced Statistical Methods for Data Fusion, Interpretation and Calibration. An important direction of future work will focus on investigating the applicability of statistical and machine learning methods to better interpret the available data. For instance, the bar codes and consistency measures discussed in Section 5 have been very useful in supporting the current practice, but also have shortcomings; e.g., if you calculate the consistency of individuals, and several students score 81%, this hardly implies that these students are at the same level of performance: the observations below the threshold could relate to minor or serious issues, and their distribution over time could be very different. Therefore, we need mechanisms to look at the patterns, and their causes, to help inform staff of whose progress is on schedule and whose might pose a problem.. This line of work could lead to novel definitions of metrics such as consistency of learner performance that are better supported by the available data themselves. Another interesting question here is whether it is possible to come up with better methods for calibration of the interrelated strictness of different teachers, hardness of different tasks, and skill of different students.

Adaptive Tutoring. In its current form, LiftUpp already supports some amount of adaptivity in the roster of the students as discussed earlier in Section 5. Future research, however, could focus on building on intelligent tutoring systems research to more intelligently select next procedures to perform. Additionally, such adaptive elements could also be supported at a much finer level. For instance, one can conceive of an approach where the system knows what the student has been doing in the clinic and then intelligently issues a series of questions through adaptive testing approaches that contextualise the knowledge, which the student is required to answer there and then in the clinic. Over time, this would reinforce the association between the knowledge base and its practical application.

Personalized Feedback and Student Advice. At a coarser level, such approaches will be useful to assist in advising students. Staff can be variable in their ability to give feedforward advice. Good advice is predicated around sets of principles that are evidence based. Through analysis of student performance data we think it will be possible to give well constructed development advice personalised to the learner. Similarly, one can imagine the use of such data analyses for advising over the need for a trajectory change, or the need to experience particular contexts. This is essential for the development of self-regulated learning. But in the extreme, since the cost to the tax payer per dental student is £250K, it is better for both the students and public to know early if they are not going to make it.

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