Interactive Technology and Smart Education

Emerging challenges in digital learning environments

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Challenges of implementing data analytics in productive education systems for supporting cognition and exploratory learning in 21st century

Introduction
The current state of implementation of data analytics in education institutions may be a paradoxical exercise. World-class experts in data science, information systems, management and education may be part of the institution. However, these experts may only have loose insights into the requirements of data analytics or digital learning when it comes to questions of implementation. Still, the link between available data, analytics and digital systems are globally investigated for their potential to transform learning, teaching and assessment towards offering unique learning experiences to the twenty-first century learners. Questions focussing on the implementation of data analytics and digital learning in productive educational systems have been addressed at the Cognition and Exploratory Learning in the Digital Age (CELDA; www.celda-conf.org) conference series for more than 10 years.

CELDA is a unique international research conference that brings together educational technology and educational psychology researchers, as well as instructional designers and other educational practitioners for the purpose of fostering and promoting ongoing dialogue between these academic and professional communities. CELDA is sponsored by the International Association for the Development of the Internet Society (www.iadisportal.org).

CELDA has created, since it was initiated in 2004, a community that has contributed to outcomes in the form of special issues published in academic journals (Ifenthaler et al., 2012b, 2009, 2015, 2018, 2012a, 2014; Kinshuk et al., 2010; Kinshuk and Sampson, 2006; Kinshuk et al., 2007, 2008; Sampson et al., 2014; Spector et al., 2016a, 2009) and edited books that inform and influence academic and professional practice (Ifenthaler et al., 2011; Isaias et al., 2012, 2015; Sampson et al., 2014, 2018, 2013; Spector et al., 2010, 2016b).

This special issue based on papers presented in CELDA 2017 is the most recent outcome of this well-established process. It is created from the extended versions of the best papers around a core theme from the 2017 International Conference on CELDA (www.iadisportal.org/celda-2015-proceedings) that was held in Vilamoura, Algarve, Portugal, in October 2017. Each contribution reports an original research work in the theme of this special issue – “Challenges of implementing data analytics in productive education systems for supporting cognition and exploratory learning in 21st century”.

Contributors to this special issue
The special issue starts with a paper by Dirk Tempelaar (Maastricht University), Bart Rientsies (Open University) and Quan Nguyen (Open University) that demonstrates how the combination of trace data derived from technology-enhanced learning environments and self-response survey data can contribute to the investigation of self-regulated learning processes. Findings of “A multi-modal study into students’ timing and learning regulation: time is ticking” show that in a blended setup, one needs to distinguish the grand effect on learning from the partial effect on learning in the digital mode: the most adaptive students might be less dependent for their learning on the use of the digital learning mode.
“Real-time learning analytics system for improvement of on-site lectures” by Atsushi Shimata (Kyushu University), Shin’ichi Konomi (Kyushu University) and Hiroaki Ogata (Kyoto University) proposes a real-time lecture supporting system. The setting are on-site classrooms where teachers give lectures and students learn through teachers’ explanations or while working on exercises. Findings indicate that teachers are able to adjust the speed of their lecture based on the real-time feedback system, which also resulted in encouraging students to interact using bookmarks and highlights on keywords and sentences.

Matthias Kuhnel (University of Mannheim), Luisa Seiler (Baden-Wuerttemberg Cooperative State University), Andrea Honal (Baden-Wuerttemberg Cooperative State University) and Dirk Ifenthaler (University of Mannheim and Curtin University) investigate the usability of MyLA (My Learning Analytics) app prototype. “Mobile learning analytics in higher education: usability testing and evaluation of an app prototype” provides insights into the MyLA app design which targets to improve learning processes at higher education institutions. MyLA provides ubiquitous communication in form of short messages from students to their lecturer and vice versa. This is especially useful for dual system courses where students are often away from the campus.

“Using mobile devices to support cognitive apprenticeship in clinical nursing practice – a case study” by Chin-Yuan Lai (National Taichung University of Science and Technology) and Yung-Chin Yen (Tainan First Senior High School) aims to illustrate how mobile devices could be applied to substantiate cognitive apprenticeship model to optimise nursing students’ learning experiences in clinical settings. Findings show that the use of the mobile technology promotes the effectiveness of cognitive apprenticeship model, especially for processes of reflection, coaching, scaffolding and articulation.

Concluding this special issue is a paper by Maria Cutumisu (University of Alberta), examining the impact of the informational value of feedback choices on students’ performance. The “Informational value of feedback choices for performance and revision in an assessment game” suggests that critical uninformative feedback is associated with students’ performance and critical informative feedback is associated with their learning strategies. The findings may support the design and implementation of agents for providing adaptive feedback in digital learning environments.

Overall, these five selected papers in this special issue demonstrate multiple perspectives and approaches on implementing data analytics and digital learning in productive systems of educational institutions. We are hopeful that this special issue contributes in a substantive way to the discourse and research with regard to advanced technologies and innovative approaches to learning and teaching in the twenty-first century.

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References


A multi-modal study into students’ timing and learning regulation: time is ticking

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Abstract
Purpose – This empirical study aims to demonstrate how the combination of trace data derived from technology-enhanced learning environments and self-response survey data can contribute to the investigation of self-regulated learning processes.

Design/methodology/approach – Using a showcase based on 1,027 students’ learning in a blended introductory quantitative course, the authors analysed the learning regulation and especially the timing of learning by trace data. Next, the authors connected these learning patterns with self-reports based on multiple contemporary social-cognitive theories.

Findings – The authors found that several behavioural facets of maladaptive learning orientations, such as lack of regulation, self-sabotage or disengagement negatively impacted the amount of practising, as well as timely practising. On the adaptive side of learning dispositions, the picture was less clear. Where some adaptive dispositions, such as the willingness to invest efforts in learning and self-perceived planning skills, positively impacted learning regulation and timing of learning, other dispositions such as valuing school or academic buoyancy lacked the expected positive effects.

Research limitations/implications – Due to the blended design, there is a strong asymmetry between what one can observe on learning in both modes.

Practical implications – This study demonstrates that in a blended setup, one needs to distinguish the grand effect on learning from the partial effect on learning in the digital mode: the most adaptive students might be less dependent for their learning on the use of the digital learning mode.

Originality/value – The paper presents an application of embodied motivation in the context of blended learning.

Keywords Blended learning, Dispositional learning analytics, E-tutorials, Learning dispositions, Learning regulation, Learning timing

Paper type Research paper

Introduction
Blended learning and other types of technology-enhanced education offer unique opportunities to investigate traditional, educational research questions from new perspectives: “The advance of technology-enhanced learning environments is opening up new opportunities for reconstructing and analysing students’ learning behavior” (Schumacher and Ifenthaler, 2018, p. 397). The use of multi-modal data, which are characterized by two or more distinct types of data, offers new insights into the long-standing academic debates that have been addressed in the past with empirical studies based on survey data only. The availability of trace data derived from the use of
technology-enhanced learning, trace data of both process and product types (Azevedo et al., 2013), is a crucial aspect in this progress made in analysing learning behaviours. Learning analytics (LA) methods, which use “dynamic information about learners and learning environments, assessing, eliciting and analysing it, for real-time modelling, prediction and optimization of learning processes, learning environments and educational decision-making” (Ifenthaler, 2015), have boosted the use of trace data in research applications. However, most “classical” LA research suffers from the same shortcomings as classical educational research: they often use only one type of data, this time trace data, and thus focus on one single perspective.

Recently, several multi-modal studies have started to integrate different types of LA data, as well as exploring learning from intertemporal perspectives. Examples of studies applying multi-modal data are Duffy and Azevedo (2015), analysing goal-setting survey data in combination with trace data, or Sergis et al. (2018), analysing self-determination-based motivational survey data in combination with trace data. A related approach is that of dispositional learning analytics (DLA; Buckingham Shum and Deakin Crick, 2012) that proposes an infrastructure that combines learning data (generated in learning activities through technology-enhanced systems) with a broad range of learner data: student dispositions, values and attitudes measured through self-report surveys. Learning dispositions represent individual difference characteristics that impact all learning processes and include affective, behavioural and cognitive facets (Rienties et al., 2017). Students’ preferred learning approaches are examples of such dispositions of both cognitive and behavioural type. In a series of studies (Nguyen et al., 2016; Tempelaar et al., 2015, 2017a, 2017b, 2018), we have analysed bi-modal data derived from a first-year introductory course of mathematics and statistics, offered in blended mode, in which were applied several survey instruments that cover learning dispositions thought to be important in self-regulated learning. Identifying students’ preferences for alternative feedback modes, distinguishing between learners who prefer worked-out examples, tutored problem-solving or untutored problem-solving and investigating the role of learning dispositions as an antecedent of these preferences was one of the aims of these studies. In our current paper, we continue this line of research, whereby we now focus on learning regulation and especially the timing of learning as part of a self-regulated learning process and investigate the role of antecedents in this regulation, thereby focusing on antecedents that are part of the framework of embodied motivation (Spector and Park, 2018).

Self-regulated learning and the timing of learning
There is an abundance of empirical research investigating learning time in self-regulated learning processes. Examples of such studies can be found in the domain of classical educational studies such as Wolters et al. (2017) who find that students’ self-perceptions of time management are associated with self-perceived motivational and strategic aspects of self-regulated learning. Time management is also investigated in LA-based studies applying trace data, such as in Duffy and Azevedo (2015) who find that learning time invested in self-regulated learning depends on the feedback mode students are put in. However, studies focusing on the timing of learning, rather than the time of learning, seem to be scarce: irrespective of how much time students learn, how do they regulate the timing of learning time and what antecedents can explain these timing decisions?

An exception to this pattern is the Nguyen et al. (2018) study that looks into students’ timing of engagement with learning activities in an online, Open University module. The main aim of the study was to compare the learning design of an environmental management course with actual timing decisions of the students. The main conclusion was that large
differences existed in the extent to which students kept track of the “official” course agenda and that individual differences in time management went hand-in-hand with individual differences in course performance. The Nguyen et al. (2018) study was based on trace data of students’ behaviour linked with learning activities designed by teachers: process-data relating learning-time decisions of what and when to study and product-data relating course performance (i.e. passing various assessments and a final exam). In our current study, we aim to link similar behavioural data as used in that study, the timing decisions made in the learning process, with learning disposition data measured through surveys, to be able to compose alternative characterizations of students who prepare in time, as well as students who tend to postpone.

Candidates for learning dispositions that might play a role in the explanation of learning timing decisions in a self-regulated learning context are manifold. From a theoretical perspective, Schumacher and Ifenthaler (2018) decomposed the cyclical self-regulated learning process into three components, the cognitive, metacognitive and motivational components, each counting several learner characteristics or dispositions. Starting from a more practical perspective, asking first-year students about their expectations with regard to the staff support in the development of academic competencies, Mah and Ifenthaler (2018) found five classes of competencies that students aimed to develop with the support of staff: time management, learning skills, technology proficiency, self-monitoring and research skills, which are easily mapped into the three components. In this study, we have opted to apply a broad range of instruments measuring learning disposition relevant to self-regulated learning, covering all three components and most of the reported competencies.

The two main research questions we adopted in this study build on the above-cited studies, whereby we specifically have identified sub-questions to unpack the complex, intertemporal decisions that students make when learning in our blended learning context:

\[ RQ1 \]. How can we explain timing decisions by students about when and what to study in a blended mathematics and statistics course?

\[ RQ1a \]. To what extent do learning regulation and timing matter, and how do they predict course performance?

\[ RQ1b \]. To what extent can the four control variables (i.e. the three dummy variables: sex, Dutch secondary education, advanced mathematics in secondary education and score on a diagnostic entry test) explain variation in the amount of preparation and the timing of preparation?

To be able to disentangle the effects of the cognitive, metacognitive and motivational components, we present the outcomes relating to five distinct and unique survey instruments that conceptualize learning dispositions as separate sub-questions. In terms of \( RQ2a \), we combine cognitive and metacognitive antecedents as developed by the Student Approaches to Learning (SAL) framework by Vermunt (1996) to unpack the impact on learning regulation. We include two aspects of SAL: cognitive processing strategies and metacognitive regulation strategies, from Vermunt’s (1996) learning approaches instrument, encompassing aspects of cognitions and behaviours. Vermunt’s framework of learning approaches distinguishes four main styles or approaches: meaning-directed, application-directed, reproduction-directed and undirected learning. Each approach is based on student characteristics in four different domains: cognitive processing strategies (what students do), metacognitive regulation strategies (how students plan and monitor learning), learning orientations (why students learn) and learning conceptions (how students see learning). \( RQ2a \) focuses on the first two of these
four domains of the Inventory of Learning Styles (ILS). The processing strategies scales shaping the first domain represent Deep approaches to learning as the one pole, characterized by critical processing, relating and structuring, to Stepwise or surface approaches to learning as the opposite pole, characterized by memorizing and analysing. A third strategy is that of Concrete or strategic learning: making new knowledge concrete and applying it. The metacognitive regulation strategies that constitute the second domain describe how students regulate their learning processes. Students are positioned in the spectrum from self-regulation as the main mechanism, to external regulation. The scales are Self-regulation of learning processes and learning content, External-regulation of learning processes and learning results and Lack of regulation (Tempelaar et al., 2015, 2018; Vermunt, 1996):

RQ2. What learning dispositions act as antecedents for these timing decisions, in other words students’ learning regulation?

RQ2a. How do SAL impact learning regulation?

The second factor that we consider is educational motivation, thereby following the embodied motivation approach described in Spector and Park (2018). In that approach, motivation has a multidimensional character, forms an integrated framework including affective, physical and cognitive factors. This embodied motivation encompasses several motivational perspectives described in the literature. Three of these have been adopted in this study and are elaborated in the remainder of this section: intrinsic and extrinsic motivation, control-value theory and motivation and engagement.

Afterwards, building on the well-known self-determination theory (Deci and Ryan, 2000), we explore the role of academic motivation on learning regulation in RQ2b. Academic motivations refer to the first and second so-called mini-theories of self-determination theory: the cognitive evaluation theory, concerning intrinsic motivation, and the organismic integration theory, concerning various forms of extrinsic motivation (Deci and Ryan, 2000; Sergis et al., 2018). The second mini-theory implies that different forms of extrinsic motivation together shape a continuum with pure intrinsic and pure extrinsic motivation as the poles, describing different degrees of internalizing extrinsic motivation into mixed states of more or less learner autonomy. The instrument Academic Motivation Scale (AMS) (Vallerand et al., 1992), based upon Deci and Ryan’s (2000) model of intrinsic and extrinsic motivation, consists of items to which students respond to the question stem “Why are you going to college?” There are seven subscales on the AMS, of which three belong to intrinsic motivation scale (intrinsic motivation: to know, to accomplish and to experience stimulating sensations) and three constitute a motivational continuum reflecting the degree of self-determination to externally controlled behaviour (identified, introjected and external regulation). The last scale, a-motivation, constitutes a position away from the continuum: the absence of regulation, either externally directed or internally. In line with most empirical research, and to prevent collinearity, the seven scales are aggregated into Autonomous motivation (the sum of the three intrinsic motivation scales and identified regulation), Controlled motivation (the sum of introjected and external regulation) and A-motivation:

RQ2b. How does academic motivation based upon self-determination impact learning regulation?

Afterwards, we explore the impact of the motivation and engagement wheel of Martin (2007) on learning regulation in RQ2c. Martin (2007) breaks down learning cognitions and learning behaviours into four categories of adaptive versus maladaptive types and cognitive versus
behavioural types. The classification is based on the theory that thoughts and behaviours can both enable learning: act as boosters, as well as hinder learning: act as mufflers and guzzlers. The instrument Motivation and Engagement Wheel (Martin, 2007) provides an operationalization of the 4 higher-order factors into 11 lower-order factors. Self-belief, Value of school and Learning focus shape the adaptive, cognitive factors or cognitive boosters. Planning, Task management and Persistence shape the behavioural boosters. Mufflers, the maladaptive, cognitive factors are Anxietymotiv, Failure avoidance and Uncertain Control, while Self-sabotage and Disengagement are the maladaptive, behavioural factors or guzzlers.

To this framework, we have added Academic buoyancy from a later publication (Martin and Marsh, 2008). See Tempelaar et al. (2015, 2018) for further elaboration:

RQ2c. How does the motivation and engagement framework of learning cognitions and behaviour impact learning regulation?

The third conceptualization of educational motivation taken from Spector and Park’s (2018) embodied motivation framework is adopted in RQ2d. The Control-Value Theory of Achievement Emotions (CVTAE, Pekrun, 2006) postulates that emotions that arise in learning activities differ in valence, focus and activation. Emotional valence can be positive (enjoyment) or negative (anxiety, hopelessness and boredom). CVTAE describes the emotions experienced about an achievement activity (e.g. boredom experienced while preparing homework) or outcome (e.g. anxiety towards performing at an exam). The activation component describes emotions as activating (i.e. anxiety leading to action) versus deactivating (i.e. hopelessness leading to disengagement). From the Achievement Emotions Questionnaire (AEQ; Pekrun et al., 2011) measuring learning emotions we selected four scales: positive activating emotion Enjoyment, negative activating emotion Anxiety, neutral deactivating Boredom and negative deactivating Hopelessness. Next, Academic Control is included as the antecedent of all learning emotions. Learning emotions of epistemic type are related to cognitive aspects of the task itself (Pekrun, 2012). Prototypical epistemic emotions are curiosity and confusion. In this RQ2c, epistemic emotions were measured with the Epistemic Emotion Scales (EES, Pekrun and Meier, 2011), including Surprise, Curiosity, Confusion, Anxiety, Frustration, Enjoyment and Boredom. See Tempelaar et al. (2015, 2018) for further elaboration:

RQ2d. How do learning emotions impact learning regulation?

Finally, we explored the potential role of four economic behavioural attitudes on learning regulation in RQ2e. These attitudes, part of “other aspects of a person” in the Spector and Park (2018) framework of embodied motivation, were measured in the context of a microeconomics experiment in the same sample but appeared being of relevance to our educational research too. These attitudes are RiskTaking, the tendency to seek risk rather than avoid risk; PostponeActivities, the tendency to postpone activities; TimePrefMoney, the willingness to postpone a financial reward for a higher one in the future; and GiveUp, the willingness to give up today to benefit in the future:

RQ2e. How do attitudes in economic behaviour impact learning regulation?

Methods

Context of the empirical studies

This study takes place in a large-scale introductory mathematics and statistics course for first-year undergraduate students in a business and economics programme in The Netherlands. The educational system is best described as “blended” or “hybrid”. The main
component is face-to-face: problem-based learning (PBL), in small groups (14 students), coached by a content-expert tutor (see Williams et al., 2016 for further information on PBL and the course design). Participation in tutorial groups is required. Optional is the online component of the blend: the use of the two e-tutorials SOWISO (https://sowiso.nl/) and MyStatLab (MSL) (Tempelaar et al., 2015, 2017b). This design is based on the philosophy of student-centred education, placing the responsibility for making educational choices primarily on the student. As most of the learning takes place during self-study outside class through the e-tutorials or other learning materials, class time is used to discuss the solving of advanced problems. Thus, the instructional format is best characterized as a flipped-classroom design (Isaías et al., 2017; Sergis et al., 2018; Williams et al., 2016). Using and achieving good scores in the e-tutorial practice modes is incentivized by providing bonus points for good performance in quizzes that are taken every two weeks and consist of items that are drawn from the same item pools applied in the practical mode. This approach was chosen to encourage students with limited prior knowledge to make intensive use of the e-tutorials.

The subject of this study is the full 2017/2018 cohort of students (1027 students who had enrolled the MSL tutorial). A large diversity of the student population was present: only 20.5 per cent were educated in the Dutch high school system. Regarding nationality, the largest group, 33.5 per cent of the students, was from Germany, followed by 24.9 per cent Dutch and 19.5 per cent Belgian students. In total, 55 nationalities were present. A large share of students was of European nationality, with only 4.7 per cent of students from outside Europe. High school systems in Europe differ strongly, most particularly in the teaching of mathematics and statistics. For example, the Dutch high school system has a strong focus on the topic of statistics but is mostly missing in high school programmes of other countries. Therefore, it is crucial that this present introductory module is flexible and allows for individual learning paths (Williams et al., 2016). In this course, students spend on average 23.3 h in MSL, which is nearly 30 per cent of the available time of 80 h for learning on the topic.

On the basis of this design, this study distinguishes three learning phases. The first learning phase prepares for the tutorial session. It is not formally assessed, other than that such preparation allows students to actively participate in the discussion of the problem tasks in the tutorial session. The next phase is the preparation of the quiz session, one or two weeks later, and the third phase consists of the preparation of the final exam, at the end of the course. These later two phases do include formal assessments. Students’ timing decisions, therefore, relate to the amount of preparation in each of the three consecutive phases.

Instruments and procedure

The empirical analyses described in this contribution focus on the use of the MSL e-tutorial for learning statistics. Although Pearson MyLabs can be used as a learning environment in the broad sense of the word (it contains, among others, a digital version of the textbook), they represent primarily an environment for test-directed learning and practising. Each step in the learning process is initiated by a question, and students are encouraged to (try to) answer each question. If a student does not master a question, she/he can either ask for help to solve the problem step-by-step (Help Me Solve This) or ask for a worked example (View an Example), as demonstrated in Figure 1 (left panel), in any lesson.

Students can call for multiple examples that differ in the context of the application of the same statistical principle, as indicated by the theory of example-based learning (Figure 1, right panel). When after studying these examples the student feels ready to make an attempt
on his/her own, a new version of the problem loads (parameter based) to allow the student to demonstrate his/her newly acquired mastery.

Our study combines trace data of the MSL e-tutorial with self-report survey data measuring learning dispositions. Trace data are both of product and process type (Azevedo et al., 2013). MSL reporting options for trace data are very broad, requiring making selections from the data. First, all dynamic trace data were aggregated over time to arrive at static, full course period accounts of trace data. Second, from the large array of trace variables, a selection was made by focussing on process variables most strongly connected to timing decisions students take. In total, we selected five trace variables:

1. **FinalMastery**: Mastery at the end of the course, at the moment students write the exam: the proportion of the total 160 exercises successfully answered;
2. **TutorialPrep**: Mastery in the first learning phase, measured at the start of the weekly tutorial sessions;
3. **QuizPrep**: Mastery in the second learning phase, measured at the start of the biweekly quiz sessions;
4. **Tutorial%**: Percentage of **FinalMastery** achieved in the first learning phase, as preparation of the tutorial session; and
5. **Quiz%**: Percentage of **FinalMastery** achieved in the first and second learning phase, as preparation of the quiz session.

As tutorial sessions and quiz sessions take place at different times, we proxy the learning taking place in Phases 1 and 2 by including all learning till the start of the last session, making use of the pattern that most students prepare immediately before sessions taking place, but not immediately after their sessions. **FinalMastery** (exam preparation, learning in all three phases together) is strongly collinear with **QuizPrep** and slightly less collinear with **TutorialPrep**. That collinearity is the result of the cumulative nature of these three mastery scores: quiz preparation equals tutorial session preparation plus additional preparation in between tutorial session and quiz, and exam preparation equals quiz preparation plus additional preparation after the quiz session. To diminish collinearity, and to disentangle the effects of learning intensity from the effects of learning timing, we re-expressed the two variables **TutorialPrep** and **QuizPrep** as percentages of final mastery, rather than as absolute mastery levels. That way, **Tutorial%** is the percentage of the final mastery achieved...
in the first phase, measured at the start of the tutorial session, and Quiz% is the percentage of the final mastery achieved in the first and second phases, measured at the start of the quiz session. Table I provides descriptive statistics of trace variables.

As can be seen from Table I, students focus their preparations more on the quiz session than the tutorial session: the largest jump in mastery is in between these two sessions. But, there exist strong individual differences in timing: some students are fully prepared for the tutorial sessions, others not at all. These individual differences result in skewness in all of the variables: negative skewness in case of quiz or exam preparation (because of a ceiling effect) and positive skewness in case of tutorial preparation (floor effect). Logarithmic transforms do improve skewness scores. However, regression models as estimated in the several partial studies appear practically invariant for these transforms, and therefore, we retain the untransformed variables, for ease of interpretation of the regression outcomes.

The statistical method applied in each of the separate studies is that of hierarchical regression analysis, with the aim to discover how well timing-related trace data predict course performance, and how well learning dispositions predict timing-related trace data. As explained above, we restrict to linear regression models. For all models, we report standardized regression coefficients (beta), significance levels (sign.) and explain variation as $R$ and $R^2$. All regression models contain three control variables that aim to account for differences between students at the start of the course:

- **Sex**: Dummy variable indicating female students (43 per cent of the students), with male students as the base value.
- **DutchEduc**: Dummy variable indicating students with a Dutch high school diploma: 20 per cent. In the mathematics programme of the Dutch high school system, there is a strong emphasis on statistics. This dummy is different from the nationality dummy, as quite some Dutch students have a prior education of international type.
- **MathAdv**: Dummy variable indicating students who learned mathematics at an advanced level in high school (preparing for sciences and technical studies): 33 per cent of students. All other students enjoyed mathematics at the intermediate level (preparing for social sciences), as students with only mathematics at the basic level are not admissible.
- **StatsEntry**: Score on a diagnostic entry exam taken at the start of the course.

The measurement of learning dispositions as applied in the several studies takes place at the start of the course. The exceptions are both types of learning emotions that are measured about halfway through the course, to be sure that students have a proper conception of the topics and type of tasks they are asked about.

<table>
<thead>
<tr>
<th>Trace variables</th>
<th>Mean (%)</th>
<th>SD (%)</th>
<th>Skewness</th>
</tr>
</thead>
<tbody>
<tr>
<td>TutorialPrep</td>
<td>21.8</td>
<td>25.6</td>
<td>1.21</td>
</tr>
<tr>
<td>QuizPrep</td>
<td>52.3</td>
<td>28.4</td>
<td>-0.23</td>
</tr>
<tr>
<td>FinalMastery</td>
<td>57.7</td>
<td>28.2</td>
<td>-0.50</td>
</tr>
<tr>
<td>Tutorial%</td>
<td>30.1</td>
<td>30.9</td>
<td>0.93</td>
</tr>
<tr>
<td>Quiz%</td>
<td>90.8</td>
<td>20.4</td>
<td>-1.62</td>
</tr>
</tbody>
</table>

**Table I.** Descriptive statistics of the trace variables
RQ1a: learning regulation and performance

Do timing decisions matter? In RQ1a, we investigate the relationship between students’ learning regulation and course performance, to find out if the timing of learning and the amount of preparation for tutorial and quiz sessions have any impact on how well students perform in the course.

Course performance data are based on the final written exam, as well as the three biweekly, intermediate quizzes. Quiz scores are averaged, and for the exam as well as quizzes we focus on the statistics topic scores: StatsExam and StatsQuiz. Table II describes the regression models for these two performance components.

Three out of four of the control variables have a significant effect: coming from Dutch prior education, being taught mathematics at the highest level and having high statistics proficiency as measured with the entry test. There is no gender effect. The strongest predictor of performance is, however, the final mastery level in the tool. In itself, it explains 45 per cent of the variation in the quiz scores and 15 per cent of the variation in exam scores. Whereby, timing represented by Tutorial% and Quiz% appears to be important too: the earlier, the better. This is because the effects are cumulative: the mastery matters, the part of mastery learned before the quiz matters with an extra multiplier and the part mastered before the tutorial session with again an extra multiplier. Differences exist between the two types of performance: for the quiz scores, there is no significant multiplier for the learning taking part in the first phase, the preparation for the tutorial session. Thus, timing is relevant only to the extent mastery is achieved before the quiz takes place, but for exam scores, students benefit both from learning in the second phase, preparing for the quiz session, as well as learning in the first phase, preparing for the tutorial session.

RQ1b: controls and learning regulation

To what extent can the four control variables that describe individual differences at the start of the course explain variation in the amount of preparation and the timing of preparation? Table III describes the three regression equations with control variables as the sole predictors.

The role of the control variables in explaining learning regulation differs from their role in course performance. Female students practice more and do better in terms of time: all positive and significant betas. Students with a Dutch prior education having better prior knowledge, practice less, certainly in the first learning phase, and somewhat compensate that in the second learning phase. Students who took advanced mathematics, and students with higher levels of prior proficiency, do reach higher mastery levels and do so in a timelier manner.

<table>
<thead>
<tr>
<th>Dispositions</th>
<th>StatsExam Beta</th>
<th>Sign.</th>
<th>StatsQuiz Beta</th>
<th>Sign.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>-0.024</td>
<td>0.415</td>
<td>-0.009</td>
<td>0.708</td>
</tr>
<tr>
<td>DutchEduc</td>
<td>0.097</td>
<td>0.001</td>
<td>0.107</td>
<td>0.000</td>
</tr>
<tr>
<td>MathAdv</td>
<td>0.098</td>
<td>0.001</td>
<td>0.073</td>
<td>0.001</td>
</tr>
<tr>
<td>StatsEntry %</td>
<td>0.221</td>
<td>0.000</td>
<td>0.161</td>
<td>0.000</td>
</tr>
<tr>
<td>FinalMastery %</td>
<td>0.363</td>
<td>0.000</td>
<td>0.674</td>
<td>0.000</td>
</tr>
<tr>
<td>Tutorial%</td>
<td>0.120</td>
<td>0.001</td>
<td>0.005</td>
<td>0.857</td>
</tr>
<tr>
<td>Quiz%</td>
<td>0.146</td>
<td>0.000</td>
<td>0.252</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table II.
Regression models explaining course performance

$R = 0.561$ $R^2 = 0.315$ $R = 0.762$ $R^2 = 0.581$
**RQ2a: learning approaches and learning regulation**

Table IV provides the estimates of the regression model containing cognitive and metacognitive factors of SAL.

The effects of learning approaches, beyond the controls, appear to be quite modest. Regarding mastery level achieved: concrete or strategic learners focus less on the digital learning environments than deep and surface learners, as do students who lack learning regulation. Regarding the timing of the preparation: there is only an impact on the amount learned in the first phase, preparation for the tutorial sessions, where externally regulated students tend to be more timely, and self-regulated students tend to be less so.

**RQ2b: self-determination-based academic motivation and learning regulation**

Table V describes the regression model of the self-determination constructs.

Although Autonomous motivation is significantly positively related to both FinalMastery and Tutorial%, these correlations do not show up in the regression models as significant betas: the effects are absorbed in the controls. It remains only a negative effect of A-motivation on total mastery and on the share of mastery achieved in the first learning phase, implying that a-motivated learners both practice less and later.

**RQ2c: motivation and engagement wheel and learning regulation**

The regression outcomes for the motivation and engagement wheel by Martin (2007) are illustrated in Table VI.

---

**Table III.** Regression models explaining learning regulation from controls

<table>
<thead>
<tr>
<th>Dispositions</th>
<th>FinalMastery</th>
<th></th>
<th>Tutorial%</th>
<th></th>
<th>Quiz%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>0.116</td>
<td>0.001</td>
<td>0.123</td>
<td>0.000</td>
<td>0.095</td>
</tr>
<tr>
<td>DutchEduc</td>
<td>-0.136</td>
<td>0.000</td>
<td>-0.153</td>
<td>0.000</td>
<td>0.078</td>
</tr>
<tr>
<td>MathAdv</td>
<td>0.099</td>
<td>0.003</td>
<td>0.015</td>
<td>0.665</td>
<td>0.079</td>
</tr>
<tr>
<td>StatsEntry %</td>
<td>0.146</td>
<td>0.000</td>
<td>0.034</td>
<td>0.330</td>
<td>-0.002</td>
</tr>
<tr>
<td>R</td>
<td>0.230</td>
<td></td>
<td>0.196</td>
<td></td>
<td>0.143</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.053</td>
<td></td>
<td>0.038</td>
<td></td>
<td>0.020</td>
</tr>
</tbody>
</table>

---

**Table IV.** Regression models explaining learning regulation from learning strategies

<table>
<thead>
<tr>
<th>Dispositions</th>
<th>FinalMastery</th>
<th></th>
<th>Tutorial%</th>
<th></th>
<th>Quiz%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>0.076</td>
<td>0.029</td>
<td>0.110</td>
<td>0.002</td>
<td>0.100</td>
</tr>
<tr>
<td>DutchEduc</td>
<td>-0.152</td>
<td>0.000</td>
<td>-0.162</td>
<td>0.000</td>
<td>0.073</td>
</tr>
<tr>
<td>MathAdv</td>
<td>0.095</td>
<td>0.004</td>
<td>0.014</td>
<td>0.669</td>
<td>0.072</td>
</tr>
<tr>
<td>StatsEntry %</td>
<td>0.140</td>
<td>0.000</td>
<td>0.036</td>
<td>0.308</td>
<td>-0.007</td>
</tr>
<tr>
<td>Deep learning</td>
<td>0.023</td>
<td>0.612</td>
<td>0.049</td>
<td>0.289</td>
<td>0.085</td>
</tr>
<tr>
<td>Stepwise learning</td>
<td>0.065</td>
<td>0.133</td>
<td>0.028</td>
<td>0.527</td>
<td>-0.051</td>
</tr>
<tr>
<td>Concrete learning</td>
<td>-0.135</td>
<td>0.000</td>
<td>-0.071</td>
<td>0.097</td>
<td>-0.043</td>
</tr>
<tr>
<td>Self-regulation</td>
<td>-0.012</td>
<td>0.799</td>
<td>-0.100</td>
<td>0.033</td>
<td>-0.063</td>
</tr>
<tr>
<td>External-regulation</td>
<td>0.067</td>
<td>0.079</td>
<td>0.102</td>
<td>0.009</td>
<td>0.073</td>
</tr>
<tr>
<td>Lack of regulation</td>
<td>-0.081</td>
<td>0.017</td>
<td>-0.037</td>
<td>0.280</td>
<td>-0.040</td>
</tr>
<tr>
<td>R</td>
<td>0.310</td>
<td></td>
<td>0.247</td>
<td></td>
<td>0.181</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.096</td>
<td></td>
<td>0.061</td>
<td></td>
<td>0.033</td>
</tr>
</tbody>
</table>
This table includes two remarkable effects: those of Value of school and Academic buoyancy. Both of the variables are of the adaptive type but bring negative betas into the model: Value of school only about total amount of preparation, and Academic buoyancy about both amount and timing of preparation. Negative effects on both amount and timing of preparation of the maladaptive behaviours Self-sabotage and Disengagement are fully in line with theoretical expectations, as is the positive effect of adaptive behaviour Planning on the timing of learning.

**RQ2d: learning emotions and learning regulation**

Table VII describes the regression model of the AEQ of Pekrun et al. (2011) built with the epistemic emotions.

Two epistemic emotions have an impact on the amount and timing of learning: Anxiety and Boredom. Different from what the CVTAE predicts, both appear to be of deactivating type, where anxiety is hypothesized as being of activating type. When we focus on

<table>
<thead>
<tr>
<th>Dispositions</th>
<th>Final Mastery Beta</th>
<th>Sign.</th>
<th>Tutorial % Beta</th>
<th>Sign.</th>
<th>Quiz % Beta</th>
<th>Sign.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>0.115</td>
<td>0.001</td>
<td>0.111</td>
<td>0.001</td>
<td>0.083</td>
<td>0.018</td>
</tr>
<tr>
<td>DutchEduc</td>
<td>-0.140</td>
<td>0.000</td>
<td>-0.151</td>
<td>0.000</td>
<td>0.080</td>
<td>0.024</td>
</tr>
<tr>
<td>MathAdv</td>
<td>0.101</td>
<td>0.002</td>
<td>0.014</td>
<td>0.677</td>
<td>0.074</td>
<td>0.031</td>
</tr>
<tr>
<td>StatsEntry %</td>
<td>0.134</td>
<td>0.000</td>
<td>0.028</td>
<td>0.425</td>
<td>-0.011</td>
<td>0.753</td>
</tr>
<tr>
<td>Autonomous</td>
<td>0.038</td>
<td>0.320</td>
<td>0.041</td>
<td>0.301</td>
<td>-0.013</td>
<td>0.742</td>
</tr>
<tr>
<td>Controlled</td>
<td>-0.057</td>
<td>0.128</td>
<td>-0.023</td>
<td>0.546</td>
<td>0.010</td>
<td>0.802</td>
</tr>
<tr>
<td>A-motivation</td>
<td>-0.133</td>
<td>0.000</td>
<td>-0.074</td>
<td>0.033</td>
<td>-0.025</td>
<td>0.479</td>
</tr>
</tbody>
</table>

$R = 0.283 \quad R^2 = 0.080 \quad R = 0.216 \quad R^2 = 0.047 \quad R = 0.139 \quad R^2 = 0.011$

<table>
<thead>
<tr>
<th>Dispositions</th>
<th>Final Mastery Beta</th>
<th>Sign.</th>
<th>Tutorial % Beta</th>
<th>Sign.</th>
<th>Quiz % Beta</th>
<th>Sign.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>0.064</td>
<td>0.073</td>
<td>0.075</td>
<td>0.041</td>
<td>0.050</td>
<td>0.190</td>
</tr>
<tr>
<td>DutchEduc</td>
<td>-0.135</td>
<td>0.000</td>
<td>-0.163</td>
<td>0.000</td>
<td>0.074</td>
<td>0.040</td>
</tr>
<tr>
<td>MathAdv</td>
<td>0.095</td>
<td>0.003</td>
<td>0.010</td>
<td>0.756</td>
<td>0.062</td>
<td>0.074</td>
</tr>
<tr>
<td>StatsEntry %</td>
<td>0.109</td>
<td>0.001</td>
<td>0.028</td>
<td>0.574</td>
<td>-0.006</td>
<td>0.865</td>
</tr>
<tr>
<td>Autonomous</td>
<td>0.021</td>
<td>0.320</td>
<td>0.019</td>
<td>0.331</td>
<td>0.024</td>
<td>0.610</td>
</tr>
<tr>
<td>Controlled</td>
<td>-0.178</td>
<td>0.000</td>
<td>-0.073</td>
<td>0.113</td>
<td>0.012</td>
<td>0.803</td>
</tr>
<tr>
<td>A-motivation</td>
<td>-0.026</td>
<td>0.587</td>
<td>-0.014</td>
<td>0.784</td>
<td>0.011</td>
<td>0.835</td>
</tr>
<tr>
<td>Planning</td>
<td>0.041</td>
<td>0.293</td>
<td>0.088</td>
<td>0.032</td>
<td>0.072</td>
<td>0.088</td>
</tr>
<tr>
<td>Task management</td>
<td>0.077</td>
<td>0.063</td>
<td>0.062</td>
<td>0.150</td>
<td>-0.001</td>
<td>0.900</td>
</tr>
<tr>
<td>Persistence</td>
<td>0.056</td>
<td>0.165</td>
<td>-0.052</td>
<td>0.219</td>
<td>0.014</td>
<td>0.749</td>
</tr>
<tr>
<td>Academic buoyancy</td>
<td>-0.123</td>
<td>0.004</td>
<td>-0.107</td>
<td>0.017</td>
<td>-0.120</td>
<td>0.009</td>
</tr>
<tr>
<td>Anxietymotiv</td>
<td>-0.066</td>
<td>0.162</td>
<td>-0.086</td>
<td>0.079</td>
<td>-0.074</td>
<td>0.145</td>
</tr>
<tr>
<td>Failure avoidance</td>
<td>-0.062</td>
<td>0.097</td>
<td>-0.012</td>
<td>0.759</td>
<td>0.007</td>
<td>0.851</td>
</tr>
<tr>
<td>Uncertain control</td>
<td>0.001</td>
<td>0.972</td>
<td>0.016</td>
<td>0.706</td>
<td>-0.027</td>
<td>0.534</td>
</tr>
<tr>
<td>Self-sabotage</td>
<td>-0.121</td>
<td>0.003</td>
<td>-0.190</td>
<td>0.000</td>
<td>-0.147</td>
<td>0.001</td>
</tr>
<tr>
<td>Disengagement</td>
<td>-0.183</td>
<td>0.000</td>
<td>-0.049</td>
<td>0.286</td>
<td>0.090</td>
<td>0.057</td>
</tr>
</tbody>
</table>

$R = 0.408 \quad R^2 = 0.167 \quad R = 0.336 \quad R^2 = 0.113 \quad R = 0.233 \quad R^2 = 0.054$
achievement emotions, which relate to the emotions triggered by doing the learning tasks, this pattern does change (see Table VIII).

LBoredom is still acting as a deactivating emotion, both regarding mastery and timing, but LAnxiety now predicts timing only, not final mastery.

**RQ2e: attitudes in economic behaviour and learning regulation**

In this last RQ2e, we include four facets of economic behaviour as predictors of learning regulation. Table IX provides the regression model built on these attitudinal variables.

Students’ tendencies to postpone activities, measured in a very generic way, do clearly include learning activities: it is a strong predictor of late preparation. And with postponement comes cancellation: PostPoneActivities predicts final mastery level too, with a negative beta. Next, time preference, although measured in a financial context, impacts learning too. Students who are self-restraint, willing to wait for their reward, appear to learn more timely and learn more.

**Discussion and conclusions**

Although there is a wide body of literature on multi-modal analytics, few studies have linked various conceptualizations of self-regulation (e.g. learning approaches, motivation...
and emotions) with how students are making decisions about when and what to study in a large-scale blended mathematics and statistics module. In an attempt to decompose the amount of preparation and timing of preparation as good as possible, we reformulated our target variables as final mastery and percentages of final mastery reached in the first learning phase, preparing for the tutorial session, and in the second learning phase, preparing for the quiz session. In terms of our first main research question, we collected evidence that these variables do matter in describing the learning process: they explained 32 per cent and 58 per cent of variation in the two performance variables. The explanation of final mastery and timing variables themselves appeared more difficult. Especially, the two timing variables appeared to depend on other variables beyond the set of learning dispositions investigated in this study.

Final mastery is explained by about 5 per cent by controls. Learning dispositions add to that, where up to 17 per cent explained variation when variables from the motivation and engagement wheel are applied. Timing decisions were more difficult to predict. That was already visible from the role of the control variables: they only explained 4 per cent and 2 per cent of the variation in the two timing variables. While our previous research (Nguyen et al., 2016; Tempelaar et al., 2015, 2017a, 2017b, 2018) found that learning dispositions significantly predicted aggregate learning processes and outcomes, in this study, with more fine-grained temporal data, learning dispositions seemed to add to that but generally were not able to create the same amount of predictive power as in the mastery case. The single exception to this pattern was the case of explaining in-time preparation for the tutorial sessions: the model of the last RQ2e with only two attitudinal variables as predictors, tendency to postpone activities and time preference, which explained 19 per cent of the variation of students’ preparations in the first learning phase.

The context of this paper is a course offered in blended learning format, where students apply different modes of learning. It is from that digital mode we learn so many details by analysing trace data, but the learning in the other mode, the face-to-face mode based on PBL, stays largely unmeasured. These one-sided measurements obviously impact the models we find in several of the individual studies. Several explanatory variables that on theoretical grounds were expected to describe adaptive facets of learning behaviour appeared in the regression models with negative betas, and vice versa, some variables describing maladaptive facets of learning, turned up with positive betas. This could potentially be explained by the blended nature, with the PBL mode being the most demanding learning mode and the digital mode offering more learning scaffolds to students. “Stronger” students might have had less need for these scaffolds, in contrast to the weaker students, explaining these patterns in the use of the MSL. A good example of this phenomenon is provided by

<table>
<thead>
<tr>
<th>Dispositions</th>
<th>FinalMastery Beta</th>
<th>FinalMastery Sign.</th>
<th>Tutorial% Beta</th>
<th>Tutorial% Sign.</th>
<th>Quiz% Beta</th>
<th>Quiz% Sign.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>0.067</td>
<td>0.051</td>
<td>0.052</td>
<td>0.114</td>
<td>0.066</td>
<td>0.065</td>
</tr>
<tr>
<td>DutchEduc</td>
<td>-0.113</td>
<td>0.001</td>
<td>-0.123</td>
<td>0.000</td>
<td>0.068</td>
<td>0.056</td>
</tr>
<tr>
<td>MathAdv</td>
<td>0.079</td>
<td>0.016</td>
<td>-0.004</td>
<td>0.911</td>
<td>0.062</td>
<td>0.072</td>
</tr>
<tr>
<td>StatsEntry%</td>
<td>0.134</td>
<td>0.000</td>
<td>0.038</td>
<td>0.257</td>
<td>0.005</td>
<td>0.895</td>
</tr>
<tr>
<td>RiskTaking</td>
<td>-0.052</td>
<td>0.125</td>
<td>-0.057</td>
<td>0.079</td>
<td>-0.025</td>
<td>0.476</td>
</tr>
<tr>
<td>PostPoneActivities</td>
<td>-0.270</td>
<td>0.000</td>
<td>-0.363</td>
<td>0.000</td>
<td>-0.119</td>
<td>0.001</td>
</tr>
<tr>
<td>TimePrefMoney</td>
<td>0.119</td>
<td>0.001</td>
<td>0.124</td>
<td>0.000</td>
<td>0.122</td>
<td>0.000</td>
</tr>
<tr>
<td>GiveUp</td>
<td>0.041</td>
<td>0.213</td>
<td>0.022</td>
<td>0.492</td>
<td>-0.046</td>
<td>0.186</td>
</tr>
</tbody>
</table>

Table IX. Regression models explaining learning regulation from academic motivation.

\( R = 0.373 \quad R^2 = 0.139 \quad R = 0.434 \quad R^2 = 0.189 \quad R = 0.225 \quad R^2 = 0.050 \)
RQ2a, investigating the role of learning approaches. Self-regulation of learning predicted out-of-time preparation, whereas external regulation of learning predicted in-time preparation, without significant effects on the amount of preparation. This can only be understood as self-regulated learners deciding themselves on the timing of the learning, where externally regulated learners stuck to the scheme provided in the course manual.

Another example was offered in RQ2c, where we found that Value of school and Academic buoyancy carried negative betas, both about mastery and timing, although both of these dispositions were expected to be of the adaptive type. Apparently, these students might have focussed on learning in the face-to-face mode, less accessible for many other students who lacked these adaptive dispositions, and were less dependent on learning in the digital mode.

Behavioural, maladaptive dispositions have a less complex role to play. In this study, there were several of them, in most of the instruments: the Lack of regulation metacognitive strategy, the A-motivation scale from self-determinism, the guzzlers Self-sabotage and Disengagement from the motivation and engagement wheel and the PostPoneActivities variables demonstrated negative betas for both mastery and timing. These dispositions seemed to negatively impact the learning on a generic level, rather than influence any individual mode of learning only. In the context of the framework of embodied motivation (Spector and Park, 2018), main conclusion of this study is that the role played by the several motivation perspectives demonstrates a wide variation. For instance, learning regulation suggests to be invariant over different constellations of intrinsic and extrinsic motivation, with only a-motivation having some impact. Other perspectives, such as the control-value framework or motivation and engagement wheel, however, do have stronger impacts. Overall, this study showed that learners with different self-regulation strategies opted for a range of complex, intertemporal and blended learning decisions.

Future research should explore whether or not students’ self-regulations over time were influenced by these learning decisions, and how we as educators can provide appropriate support for students who might lack sufficient self-control.

References


**Corresponding author**
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Abstract
Purpose – The purpose of this study is to propose a real-time lecture supporting system. The target of this study is on-site classrooms where teachers give lectures and a lot of students listen to teachers’ explanations, conduct exercises, etc.
Design/methodology/approach – The proposed system uses an e-learning system and an e-book system to collect teaching and learning activities from a teacher and students in real time. The collected data are immediately analyzed to provide feedback to the teacher just before the lecture starts and during the lecture. For example, the teacher can check which pages were well previewed and which pages were not previewed by students using the preview achievement graph. During the lecture, real-time analytics graphs are shown on the teacher’s PC. The teacher can easily grasp students’ status and whether or not students are following the teacher’s explanation.
Findings – Through the case study, the authors first confirmed the effectiveness of each tool developed in this study. Then, the authors conducted a large-scale experiment using a real-time analytics graph and investigated whether the proposed system could improve the teaching and learning in on-site classrooms. The results indicated that teachers could adjust the speed of their lecture based on the real-time feedback system, which also resulted in encouraging students to put bookmarks and highlights on keywords and sentences.
Originality/value – Real-time learning analytics enables teachers and students to enhance their teaching and learning during lectures. Teachers should start considering this new strategy to improve their lectures immediately.
Keyword Learning analytics
Paper type Research paper

Introduction
Much attention has been paid to learning analytics in the technology-enhanced learning research domain. The Society for Learning Analytics and Research defined learning analytics as the measurement, collection, analysis and reporting of data about learners and their context for the purpose of understanding and optimizing learning and the
environments in which it occurs. In the early stages of learning analytics, researchers discussed methods for measuring a learning environment and collecting data. Recently, virtual learning environments and learning management systems such as Blackboard (Bradford et al., 2007) and Moodle (Dougiamas and Taylor, 2003) have enabled us to collect large-scale educational data (educational big data) easily. The latest research has focused on methods for analyzing educational big data and reporting, that is, how to provide feedback on analysis results to teachers/students.

Khalil et al. gave a survey (Khalil and Ebner, 2016) on learning analytics and divided the methods into seven categories:

1. data mining techniques – the prediction of students’ academic achievement (Asif et al., 2017), detecting students at risk using clicker responses (Choi et al., 2018) and forecasting the relation between studying time and learning performance (Jo et al., 2014);

2. statistics and mathematics – building a grading system (Vogelsang and Ruppertz, 2015) and temporal discourse analysis of an online discussion (Lee and Tan, 2017);

3. text mining, semantics and linguistic analysis – summarization of students’ learning journals (Taniguchi et al., 2017) and understanding students’ self-reflections (Kovanović, 2018);

4. visualization – comprehensive overview of students’ learning from learning management system (Poon et al., 2017), awareness tool for teachers and learners (Martinez-Maldonado et al., 2015) and a learning analytics dashboard (Aljohani et al., 2018);

5. network analysis – relationship analysis between technology use and cognitive presence (Kovanović, 2017), classification of students’ patterns into categories based on the level of engagement (Khalil and Ebner, 2016) and a network analysis of LAK (Learning Analytics and Knowledge) conference papers (Dawson et al., 2014);

6. qualitative analysis – an evaluation of discussion forums of MOOCs (Ezen-Can et al., 2015) and analyzing instructors comments (Gardner et al., 2016); and

7. gamification – e-assessment platform with gamification (Gañán et al., 2017), gamified dashboard (Freitas et al., 2017) and a competency map (Grann and Bushway, 2014).

Results of learning analytics are helpful for teachers and learners to improve their teaching and learning. Therefore, one of the important issues in learning analytics is obtaining feedback for optimizing the learning environment and learners themselves. There are roughly three types of feedback loops in terms of their frequency: yearly, weekly and real-time feedback. The above-mentioned studies are basically categorized into yearly feedback or weekly feedback types because the analyses results are not immediately fed back to on-site teachers/students who provide their educational/learning logs for the analytics. The reason is obvious – learning analytics is basically performed after classes, school terms or school years. Therefore, the feedback is delayed accordingly. However, if a real-time feedback can be obtained, then it can be very useful and helpful for teachers and students in on-site classrooms.

Our study focused on feedback – specifically, how to provide feedback – on efficient information to on-site classrooms even during lectures. The aim of this study is to realize real-time feedback, which has not often been discussed with respect to on-site educational environments. Our target is on-site classrooms where teachers give lectures and a lot of
students listen to teachers’ explanations, conduct exercises, etc. In such a large classroom, it is not easy for teachers to grasp students’ situations and activities. We utilize not only an e-learning system but also an e-book system to collect real-time learning activities during the lectures. We have developed two main feedback systems. One is useful for a teacher just before the lecture starts. The system provides summary reports of the previews of the given materials and quiz results. The teacher can check which pages were well previewed and which pages were not previewed by students using the preview achievement graph. Additionally, the teacher can check which quizzes were difficult for students, and the suggested pages that should be used in the lecture to aid students. The other is real-time analytics graphs, which are helpful for the teacher to control his/her lecture speed during the lecture. The system collects e-book logs operated by students sequentially and performs analytics in real time to determine how many students are following the teacher’s explanation. In the rest of this paper, we introduce the details of our real-time feedback system and report the experimental results.

Literature review
There are roughly three types of feedback loops in terms of their frequency: yearly, weekly and real-time feedback. A typical example of a yearly (or term-by-term) feedback loop is the assessment and improvement of education. Students’ grades, examination results, class questionnaires and so on are typically analyzed and evaluated. The relationship between self-efficacy and learning behaviors on the e-book system was analyzed (Yamada et al., 2015). Teachers receive new information that student behaviors, with regard to markers and annotations, are related to their self-efficacy and to the intrinsic value of the learning materials. Other examples of a yearly (or term-by-term) feedback loop include an analysis of students’ performance (Okubo et al., 2016) and a prediction of students’ final grade (Mouri et al., 2016). The yearly feedback loop is designed so that the feedback results will be delivered in the next year (or term). In other words, students and teachers will not directly receive the feedback results acquired by analyzing their own learning logs. The feedback could also be an analysis of learning logs collected in previous years.

A weekly feedback loop can recommend related materials based on students’ status determined using a prediction of academic performance through the analysis of learning logs such as attendance reports and quiz results. For example, the analytics of preview and review patterns (Oi et al., 2015) or learning behavior analytics (Yin et al., 2015) is helpful to understand the weekly performance of students. Text analytics technology provides summarized materials for preview (Shimada et al., 2015) and review (Shimada et al., 2016). In contrast to a yearly feedback loop, the analysis results are directly fed back to the students and teachers who provide the learning logs.

There are several related works that tackle real-time learning analytics. Minovic et al. proposed a visualization tool for teachers to track students’ learning progress in real time while in a gameplay session (Minovic and Milovanovic, 2013). Piech et al. collected tens of thousands of program codes and applied a machine learning approach to identify “sink” states of students. Feedback was obtained for students just before they were about to enter such problematic “sink” states (Piech et al., 2012). Freitas et al. discuss about the effectiveness of immediate feedback to students especially in the impact of gamification in university education (Freitas et al., 2017). Fu et al. also proposed a real-time analysis of program codes (Fu et al., 2017). They provided a learning dashboard to capture the behavior of students in the classroom and identify different difficulties faced by students. Although these studies obtained real-time feedback, the target of the analytics and its feedback were activities in virtual learning environments. In contrast, our study aims to realize real-time
feedback loops where the analysis results can be fed back to on-site students and teachers even during a lecture. A teacher can check what students are doing, for example, whether students are following the explanation or whether they are doing something not related to the lecture. A teacher can flexibly control the speed of the lecture and/or take more time for exercises rather than engaging in a nonstop talk.

Implementation

**Cyber-physical educational system**

In our university, various kinds of educational/learning logs are collected by three systems: e-learning (Moodle), e-portfolio (Mahara) and e-book (BookRoll). Students submit their reports, answer quizzes, access materials and reflect on their learning activities using these systems. More precise learning logs are collected by the e-book system, such as when a student opens some material or when he/she turns a page of the material. All students use their own laptops so that they can access these systems from anywhere, either on or off campus.

The e-book logs were collected via an e-book system called “BookRoll”. Table I shows samples of e-book logs. There are many types of operations recorded in the logs. For example, OPEN means that the student opened the e-book file, whereas NEXT means that the student clicked the next button to move to the subsequent page. The browsing duration for each page can be calculated by subtracting the subsequent timestamps. Learning logs on the e-learning system such as attendance and quiz scores are collected from tables in the Moodle database. The system analyzes the quiz scores and class attendance by integrating related tables. In this study, we mainly use the e-learning system and e-book system to realize the proposed real-time learning analytics system.

**On-site lecture supporting system**

We present the example case study shown in Figure 1, which was actually applied to a lecture in our university. The timeline is divided into two parts: before starting a class and during a class. During the previous lecture, a teacher gave students some preview materials that were automatically generated using the summarization technique (Shimada et al., 2017). Students previewed the given materials before the class, and the operation logs recorded during the previews were collected by the system. Before the class started, students answered the quizzes, and the results were collected on the server.

Just before the lecture started, our system analyzed the learning logs to make a summary report containing previews of the achievement and quiz results (details are given in Section 2.6). Additionally, the system provided information regarding important pages that should be explained well in the lecture. For example, the teacher should focus on pages that are related to quizzes, especially those that have led to lower quiz scores. Our system analyzed the relationship between quiz statements and their related pages in the lecture material in advance. Section 2.3 explains how we automatically discovered important pages.

<table>
<thead>
<tr>
<th>User</th>
<th>Material</th>
<th>Operation</th>
<th>Page no.</th>
<th>Date</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>Material A</td>
<td>OPEN</td>
<td>0</td>
<td>2014/10/15</td>
<td>9:01:09</td>
</tr>
<tr>
<td>X</td>
<td>Material A</td>
<td>CLOSE</td>
<td>1</td>
<td>2014/10/15</td>
<td>9:01:13</td>
</tr>
<tr>
<td>Y</td>
<td>Material B</td>
<td>PREV</td>
<td>25</td>
<td>2014/10/29</td>
<td>10:05:35</td>
</tr>
<tr>
<td>Y</td>
<td>Material C</td>
<td>NEXT</td>
<td>2</td>
<td>2014/11/19</td>
<td>8:52:47</td>
</tr>
<tr>
<td>Z</td>
<td>Material D</td>
<td>NEXT</td>
<td>9</td>
<td>2014/11/12</td>
<td>9:31:30</td>
</tr>
</tbody>
</table>

Table I. Sample e-book logs
During the lecture, a teacher explained the contents of the materials, and students browsed the materials on their laptops. In our university, students were asked to open and browse the same page as the teacher and to put highlights or memos on the important points. During the lecture, learning logs were sequentially collected and stored. The analysis results were immediately visualized on the web interface and updated each minute. Therefore, the teacher could check the latest student activities. The visualization included real-time information regarding how many students were following the lecture, how many students were browsing previous pages, etc. The web interface is described in Section 2.6. The teacher adaptively controlled the speed of the lecture according to the students. For example, if many students were not following the lecture and were still on the previous page, then the teacher slowed down the lecture.

**Notes:** Students previewed materials before their class and answered the quizzes. Learning logs (e-book operation logs and quiz results) were collected in the system, and summary reports were sent to the teacher. The teacher checked the preview achievements (which page was browsed the most, which page was not read, etc.) and quiz results before starting the lecture. Additionally, the teacher was told about some important pages that should be explained well in the next lecture. During the lecture, the operation logs of the teacher and students were collected and analyzed. The results were immediately visualized on the teacher’s PC. The teacher could check the students’ activities (e.g. how many students were following the lecture) and adjust the speed accordingly.

**Important page mining**
There is a strong relationship between lecture materials and quizzes because quizzes are often generated using the contents of lecture materials. Related pages are important to
understanding the contents of the materials. However, lecture materials and quizzes are stored separately or are very weakly connected in systems using subject names, for example. We can manually assess the relationship between a quiz item and its related pages, but this is not easy or realistic when the number of quiz items and/or the number of pages increase. Furthermore, if the lecture material is updated, that is, the page numbering changes, then the teacher must update the correspondence. Therefore, we developed a method that automatically determines the correspondences.

Our strategy assumes that a related page contains the same keyword as the quiz statement. Each quiz statement, $QS$, is divided into morphemes. Then, we extract the nouns $n$ $(1, \cdots, n, \cdots, N)$. For each noun $n$, a normalized histogram $h_n$ is created. Each bin $b_{u,n}$ of the histogram $h_n$ represents how many times page $u$ contains noun $n$. Note that the bins are normalized after counting the number of times noun $n$ appears in all the pages. To acquire the final results, we sum the frequencies of all nouns. We define the normalized value $r_u$ as the related score of page $u$.

Although the mining method finds pages that are highly related to a given quiz statement, it does not consider the relationships among pages. Therefore, we also apply a ranking method that assigns a ranking score to each page. This idea was inspired by VisualRank (Jing and Baluja, 2008). A ranking vector $R$ is iteratively updated using:

$$R = \alpha(S \times R) + (1 - \alpha)B$$

where $S$ is the column normalized similarity matrix, and $S_{u,v}$ measures the page similarity between pages $u$ and $v$. In this study, we simply evaluate the similarity using the L2 norm between two feature vectors represented by a bag of words (Zhang et al., 2010). $B$ is a bias vector. We use the relate score $r_u$ as an element of $B$. $R$ is repeatedly updated until it converges. $\alpha$, $(0 \leq \alpha \leq 1)$ controls the balance between the similarity matrix and the bias vector. According to the literature (Jing and Baluja, 2008), $\alpha > 0.8$ is often used in practice. After the ranking vector $R$ converges, pages that are related to important pages have larger ranking scores. We select the top $N$ ranked pages as important.

**Preview achievement**
By analyzing e-book operation logs, we can determine how long students spend previewing each page of a given material. The previewing time for each page can be easily acquired by subtracting two successive timestamps from the operation logs. Note that we ignored durations less than 3 seconds and more than 600 seconds to discard skipped and abandoned pages. Figure 2 shows an example of a visualized result of preview achievement. A teacher can check the preview status of the given materials in advance before beginning his/her lecture.

**Quiz results**
The quiz results and questions are collected from the e-learning system, and the scores are aggregated in the class. We set a threshold for the ratio of correct answers (in our implementation, we set the threshold to 50), and if the accuracy is lower than the threshold, then important pages, which are automatically mined in advance, are displayed below the summary graph. See Figure 3 for an example of the web page. A summary graph of the quiz results is followed by the quiz statements and related page information, if necessary.
Figure 2.
Example preview achievement

Notes: The horizontal axis is the page number, and the vertical axis is the time spent previewing by students.

Figure 3.
Example quiz results and related information

When the accuracy (the ratio of right answers) is lower than a given threshold, the system display the important pages related to the quiz.
Visualizer of web pages
The proposed visualizer of the analysis results was implemented as a web system. A teacher can easily access the web page from a PC. Before the lecture starts, a teacher can access the web pages that provide summary reports of the previews of given materials and quiz results, as shown in Figures 2 and 3. The teacher can check which pages were well previewed and which pages were not previewed by students using the preview achievement graph. Additionally, the teacher can check which quizzes were difficult for students and the suggested pages that should be explained in the lecture to aid students.

During the lecture, the teacher can access two kinds of real-time analytics graphs. One is the real-time heat map shown in Figure 4. The horizontal and vertical axes represent the time of day and the page number, respectively. In other words, a vertical line corresponds to the distribution of the number of students who are browsing each page. The vertical lines are updated each minute; that is, a new line is added per minute. Each cell represents the number of students. The page being explained by the teacher is highlighted by red-colored rectangles. If a brighter color (red, orange, yellow or green) is used on the page being explained by the teacher, then most students are following the teacher’s explanation. Students are asked to try to be on the same page as the teacher and to add highlights or memos if necessary. Therefore, when the distribution of the students is skewed downward, some students are still browsing previous pages. In such a case, the teacher should slow down the lecture so that students can keep up.

The other real-time analytics graph is the circular chart (left part of Figure 5), which is a summarized version of the above heat map. A teacher can take some time to check and understand the situation from the heat map. To provide a visual summary of the heat map, the second visual focuses on the ratio of three types of students: browsing previous pages (blue), browsing the same page as the teacher (green) and browsing the next pages (red). This chart is also updated each minute to display the latest status of students. The visualizer also provides a breakdown of the three types based on whether students

Notes: The horizontal axis is the time of day, and the vertical axis is the page number. A column corresponds to the distribution of the number of students browsing each page. The page explained by the teacher is highlighted by a red-colored rectangle. The heat map is automatically updated minute by minute.
previewed the page in advance (light color) or not (dark color). For example, if many students are still browsing previous pages but most of them previewed the pages in advance, and if the pages are important ones that were related to a difficult quiz, then the teacher should wait for students to catch up and explain the material slowly and carefully. Another example is that a teacher should proceed with the lecture when many students are browsing the subsequent pages and when most of them have previewed the materials in advance. In such a situation, students may get bored during a teacher’s long explanation, or some students may have finished a given exercise.

The right part of Figure 5 is a time series of the circular chart. The teacher can see the recent trends of each status. As described above, real-time analytics graphs provide an opportunity to flexibly adjust the lecture progress based on students’ status.

**Experimental results**

*Investigation of each tool*

We investigated the effectiveness of each proposed tool in two classes at our university. One was a control group (N = 58) that did not use the above system, and the other was an experimental group (N = 157) that used the system. The contents of the two lectures were completely the same. Students chose one of them according to their schedules. Therefore, the number of students was not balanced between the two classes. The class was designed to provide an introduction to information and communication technology in a number of disciplines. First-year students, including both arts and science students, attended the class, which commenced in October 2016. All the students brought their own laptops to the class.

The lecture was given by the same teacher using the same materials. The teacher used two materials: Material 1 consisted of 37 pages, and Material 2 consisted of 47 pages. The teacher began with Material 1 and moved on to Material 2 and asked students to follow the pages in the materials using bookmarks, highlights and memos. Operation logs were sequentially collected to the server, and real-time analysis was conducted. The results were fed back to the teacher minute by minute in the experimental group only. More details are
provided in Table II. We conducted a pretest to determine students’ basic knowledge of information science. There was no significant difference between the two groups.

**Synchronization**

While the teacher conducted the lecture with the students in the experimental group, he monitored the display on which the real-time analysis results were drawn. He controlled the speed of the lecture to help students keep up as much as possible. Our hypothesis in this experiment is that the students in the experimental group would open and follow the page explained by the teacher compared with those in control group. We evaluated the synchronization of the classroom, that is, how many students were on the pages that were being explained by the teacher. We counted the number minute by minute while including the allowable delay setting, which refers to the short period for accepting the delay in e-book operations.

Table III shows the ratio of synchronization of each group. For example, if we set the allowable delay to 3 minutes (i.e. if students opened the same page as the teacher within a 3-minute delay), the synchronization ratio of the experimental group was 0.7661. The score was significantly different from the score of the control group. In other allowable delay settings, the synchronization ratios of the experimental groups were higher than those of the control group. We believe that such high synchronization was realized by the lecture speed control through real-time feedback on classroom activities.

**Effectiveness of important page suggestions**

The analyses of preview status and quiz scores were conducted just before the lecture started. The system reported that most students wrongly answered two of eleven questions. The pages related to the quizzes (Page #10 of Material 1 and Page #27 of Material 2) were shown on the display, and the teacher confirmed them. Our hypothesis in this investigation is that the teacher would spend some more time on the explanation of these pages and that would result in encouraging students to leave many learning actions on the pages.

We analyzed the time duration of pages, and found out that Page #10 was opened by the teacher for 3 minutes in the experimental group and 1 minute for the control group. In addition, we analyzed the number of bookmarks, highlights and memos on the above two

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Experimental</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td># of students</td>
<td>58</td>
<td>157</td>
<td></td>
</tr>
<tr>
<td>pretest average</td>
<td>6.85 ± 2.28</td>
<td>6.99 ± 2.38</td>
<td>n.s.</td>
</tr>
<tr>
<td>e-Book logs</td>
<td>16,335</td>
<td>39,722</td>
<td></td>
</tr>
<tr>
<td>logs/students</td>
<td>281.6 ± 123.3</td>
<td>253.0 ± 129.1</td>
<td>n.s.</td>
</tr>
</tbody>
</table>

*Table II.* Detailed information on each group (n.s.: not significant)

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Experimental</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 minute</td>
<td>0.4275</td>
<td>0.5174</td>
<td>0.0403 *</td>
</tr>
<tr>
<td>3 minutes</td>
<td>0.6598</td>
<td>0.7661</td>
<td>0.0033 **</td>
</tr>
<tr>
<td>5 minutes</td>
<td>0.7508</td>
<td>0.8599</td>
<td>0.0014 **</td>
</tr>
</tbody>
</table>

*Table III.* Synchronization ratio of each group for three allowable delay lengths. *: p < 0.05, **: p < 0.01
pages, for which the teacher had emphasized his explanations. About 61 per cent of students used the functions in the experimental group, whereas about 53 per cent of the students used the functions in the control group.

Additionally, we analyzed the utilization ratios of three functions through the materials and compared the ratios between the two groups. Table IV shows that more students in the experimental group used the functions compared with the students in the control group. We believe that the students in the experimental group had enough time to use bookmarks, highlights and/or memos because the teacher emphasized his explanations for important pages with adjusting the speed of his lecture based on the real-time situation of the classroom.

Investigation of on-site lectures
We conducted other experiments in large-scale classrooms with more than 150 students in our university in April 2018. Three classes – Class 1 (N = 174), Class 2 (N = 157) and Class 3 (N = 159) – joined our experiments. We confirmed that there was no significant difference in the basic knowledge among the classes in advance. The lecture was designed to teach cyber security to first-year students. In the three classrooms, the same lecture materials were used over two weeks. All students brought their laptops to the class. Class 1 was conducted by Teacher A without a supporting system, whereas Classes 2 and 3 were conducted by Teacher B with our supporting system. Classes 1 and 2 were conducted in parallel. Class 3 was conducted just after Class 2 on the same day. In all classes, students were asked to follow the materials pages explained by the teacher and to use bookmarks, highlights and memos. The experiments mentioned above were conducted here as well.

In Classes 2 and 3, the teacher controlled the lecture speed by checking real-time heat map. Furthermore, Teacher 2 developed a better way of following the teaching plan for Class 3 by checking the distribution of the real-time heat map just after Class 2. In fact, there was a 20-minute break between Classes 2 and 3 so that the improvement could immediately be applied to the following class. Teacher B discovered several time slots when the distribution of the real-time heat map was skewed below in Class 2. Then, he checked the corresponding pages in the lecture materials and considered a new teaching strategy for the pages in Class 3. Table VIII summarizes the pages and the improvement plans that the teacher considered and took after Class 2.

Effectiveness of real-time heat map
We make a hypothesis that the real-time heat map would provide adaptive control of lecture speed, resulting in giving enough time to students to use e-book functions of bookmarks, highlights and memos. First, we investigated the utilization ratios of these three functions, that is, how often the students used these functions during the class. We counted the number of operations used by each student and evaluated the differences among classes. According to ANOVA, there was a significant difference among the classes; therefore, we conducted a t-test for possible combinations by setting a stringent level of statistical significance.

<table>
<thead>
<tr>
<th>Table IV. Utilization ratios of three functions during the lecture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Function</td>
</tr>
<tr>
<td>---------------------</td>
</tr>
<tr>
<td>Bookmarks</td>
</tr>
<tr>
<td>Highlights</td>
</tr>
<tr>
<td>Notes</td>
</tr>
</tbody>
</table>
Tables V and VI show the average number of operations for bookmarks, highlights and memos and their standard deviations (SDs) in each class. Further, Figures 6 and 7 show the visual differences of the average number of operations among the three classes. The results of the t-test are drawn as *(p < 0.05/3), **(p < 0.01/3) and ****(p < 0.001/3). Although the usage of the memo function was not different among the classes, the other functions were frequently utilized by students in Classes 2 and 3 over two weeks. In these two classes, Teacher B controlled the speed of his lecture by checking the real-time heat map. Regarding the results, we believe students left many bookmarks and highlights on each page of the lecture materials. Furthermore, the students in Class 3 tended to leave more highlights than those in Class 2. We believe these effects came from the improvement in the lecture design implemented just after Class 2 was finished. We discuss the details in the following subsection.

Second, we investigated how students followed the lecture by evaluating the page distribution by students. The evaluation was conducted by calculating the average number of pages and its SD minute by minute. The more students browsed the same page, the smaller the SD. However, if the SD was large, then this indicated that students browsed a variety of pages. Regarding the intent of the lecture design, the ideal situation was small SD because students were asked to listen to the talk given by the teacher carefully and also

<table>
<thead>
<tr>
<th></th>
<th>Class 1</th>
<th></th>
<th>Class 2</th>
<th></th>
<th>Class 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>SD</td>
<td>Average</td>
<td>SD</td>
<td>Average</td>
<td>SD</td>
</tr>
<tr>
<td>Bookmark</td>
<td>0.48</td>
<td>2.13</td>
<td>1.44</td>
<td>3.49</td>
<td>2.48</td>
<td>4.34</td>
</tr>
<tr>
<td>Highlight</td>
<td>3.19</td>
<td>7.74</td>
<td>7.34</td>
<td>13.46</td>
<td>10.32</td>
<td>14.76</td>
</tr>
<tr>
<td>Memo</td>
<td>1.20</td>
<td>3.41</td>
<td>1.02</td>
<td>3.92</td>
<td>1.20</td>
<td>3.21</td>
</tr>
</tbody>
</table>

Table V. The average number of operations and standard deviation per student in the first week

<table>
<thead>
<tr>
<th></th>
<th>Class 1</th>
<th></th>
<th>Class 2</th>
<th></th>
<th>Class 3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average</td>
<td>SD</td>
<td>Average</td>
<td>SD</td>
<td>Average</td>
<td>SD</td>
</tr>
<tr>
<td>Bookmark</td>
<td>0.23</td>
<td>1.11</td>
<td>1.70</td>
<td>4.52</td>
<td>2.05</td>
<td>3.71</td>
</tr>
<tr>
<td>Highlight</td>
<td>1.71</td>
<td>5.69</td>
<td>5.04</td>
<td>12.25</td>
<td>14.60</td>
<td>21.87</td>
</tr>
<tr>
<td>Memo</td>
<td>0.91</td>
<td>2.95</td>
<td>0.39</td>
<td>1.92</td>
<td>0.79</td>
<td>2.31</td>
</tr>
</tbody>
</table>

Table VI. The average number of operations and standard deviations per student in the second week

* Notes: *: p < 0.05/3; **: p < 0.01/3; ***: p < 0.001/3
asked to follow the pages by leaving bookmarks, highlights and memos as much as possible. The bottom parts of Figures 8 and 9 depict the period when the teacher was talking about the contents of the lecture material in each class. Teacher A (Class 1) took a longer time for giving an explanation than Teacher B (Classes 2 and 3). We calculated the average SDs over the talking period and found out the average SDs of Classes 2 and 3 were much smaller than the SD of Class 1. Table VII summarizes the details of the average SDs. In the classrooms, with our real-time heat map (Classes 2 and 3), not only the average SD but also its variance was smaller than the one in the classroom without our system (Class 1). This means that most students followed the pages over time, which resulted in students leaving more bookmarks and highlights with listening to the explanation given by the teacher.

**Figure 7.**
The average number of operations per student in the second week

**Figure 8.**
The time-series standard deviation of page-view distribution during the lecture in the first week

**Figure 9.**
The time-series standard deviation of page-view distribution during the lecture in the second week

**Notes:** *: $p < 0.05/3$; **: $p < 0.01/3$; ***: $p < 0.001/3$
Investigation of lecture improvement

In this experiment, we investigate our hypothesis that the teacher could make better lecture strategies for the upcoming lecture, resulting in better engagement of students. As mentioned above, Classes 2 and 3 were conducted by the same teacher, and Class 2 was followed by Class 3 on the same day. During the break time between the two classes, the teacher checked the heat map again and considered the improved lecture plan as shown in Table VIII. There were a total of five cases of improvement. For instance, in Cases 1 and 2, the lecture materials provided a tutorial on how to back up data and how to update software in operating systems such as iOS, Android, and Windows. In Class 2, the teacher explained all the contents sequentially. According to the real-time heat map, shown in Figure 10, the distribution was skewed downward. After Class 2, the teacher decided to allow students to read these pages by themselves based on their own environment (some students focus on iOS pages, other students focus on Android pages, etc.). As a result, students freely browsed the pages in Class 3. The bottom right part of Figure 10 shows the distribution of Class 3. The distribution seems not so different from the one of Class 2, but the number of operations, bookmarks, and highlights drastically increased in Class 3 (Table IX).

Table IX shows the number of operations – bookmark, highlight, and memo – recorded in the pages corresponding to the five cases in Table VIII. In total, the students in Class 3 tended to leave more bookmarks and highlights in the pages. Additionally, the number of students who utilized these functions also drastically increased, especially the functions of the highlights in Cases 3, 4, and 5. In these cases, the teacher used the improvement strategy to spend more time on thinking, researching, and reviewing the contents. We believe that students were naturally encouraged to put bookmarks and highlights on the keywords and sentences that they thought were important.

Conclusion

We proposed a lecture supporting system based on real-time learning analytics for on-site classrooms. Our system provided summary reports of previews and quiz scores just before a

<table>
<thead>
<tr>
<th>Case</th>
<th>Week</th>
<th>Pages</th>
<th>Contents in the pages and the improvement strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>First week</td>
<td>35-37</td>
<td>Tutorial on how to backup data in each OS (iOS/Android/Windows)</td>
</tr>
<tr>
<td>2</td>
<td>First week</td>
<td>43-55</td>
<td>Tutorial on how to update the software and applications in each OS</td>
</tr>
<tr>
<td>3</td>
<td>Second week</td>
<td>16-20</td>
<td>Password management; What is a good/bad password?</td>
</tr>
<tr>
<td>4</td>
<td>Second week</td>
<td>22</td>
<td>Introduction to password management software</td>
</tr>
<tr>
<td>5</td>
<td>Second week</td>
<td>39-42</td>
<td>Wi-Fi security; points to keep in mind</td>
</tr>
</tbody>
</table>

Table VII. The average SDs of browsed pages over the talking period

<table>
<thead>
<tr>
<th>Week</th>
<th>Class 1 Average SD</th>
<th>SD of SDs</th>
<th>Class 2 Average SD</th>
<th>SD of SDs</th>
<th>Class 3 Average SD</th>
<th>SD of SDs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st week</td>
<td>7.42</td>
<td>2.85</td>
<td>4.60</td>
<td>1.70</td>
<td>3.53</td>
<td>1.52</td>
</tr>
<tr>
<td>2nd week</td>
<td>7.31</td>
<td>2.63</td>
<td>5.01</td>
<td>1.85</td>
<td>4.95</td>
<td>2.20</td>
</tr>
</tbody>
</table>

Table VIII. Improvement strategy toward Class 3 from the reflection of Class 2
The report was helpful for teachers to check which pages were well previewed and which pages were not previewed by students using the preview achievement graph. Additionally, the teacher could check which quizzes were difficult for students. Our system automatically suggested related pages that needed to be explained in the lecture to aid students. Furthermore, real-time analytics graphs were helpful for the teacher to control his/her lecture speed during the lecture. The proposed real-time learning analytics system supported on-site lectures in the following aspects:

- The teacher could adjust the speed of his or her lecture based on the real-time feedback system.
- The teacher could emphasize important points that were misunderstood by students.
- The following effects were confirmed.
- The students could keep up with the lecture by following the pages explained by the teacher.
- Many students could put bookmarks, highlights and memos on important pages.

---

**Notes:** The distribution is skewed around pages 35-37 and 43-55. The teacher considered a new strategy to improve these parts.

---

**Table IX.** The number of operations/The number of students who utilized the function for each case

<table>
<thead>
<tr>
<th>Case</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 2</th>
<th>Class 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>7/6</td>
<td>35/28</td>
<td>40/22</td>
<td>74/27</td>
<td>13/9</td>
<td>10/9</td>
</tr>
<tr>
<td>Case 2</td>
<td>33/19</td>
<td>65/32</td>
<td>160/37</td>
<td>228/55</td>
<td>21/10</td>
<td>6/5</td>
</tr>
<tr>
<td>Case 3</td>
<td>15/11</td>
<td>18/11</td>
<td>37/11</td>
<td>139/38</td>
<td>4/2</td>
<td>13/9</td>
</tr>
<tr>
<td>Case 4</td>
<td>6/6</td>
<td>10/9</td>
<td>8/7</td>
<td>54/27</td>
<td>0/0</td>
<td>1/1</td>
</tr>
<tr>
<td>Case 5</td>
<td>32/25</td>
<td>93/62</td>
<td>71/15</td>
<td>258/48</td>
<td>7/3</td>
<td>15/10</td>
</tr>
</tbody>
</table>

---

**Figure 10.** Real-time heat map of Classes 2 and 3 in the first week.
Through the empirical investigation in the lectures of our university, we found out the positive effect. First, the teacher could confirm the students’ situation whether they could follow his lecture by checking the real-time heat map. When many students opened previous pages, the teacher could slow down the speed of lecture. The adaptive control of lecture speed provided higher synchronization between the teacher and students. We believe that high synchronization leads to the improvement of lecture satisfaction level. Additionally, in the class that used the real-time heat map, more students tended to follow the same page with smaller variance than in the class that did not use the map. The real-time heat map not only allows regulated browsing of lecture material but also gives students an opportunity to use e-book operations, such as bookmarks, highlights and memos. Second, the important page suggestion system helped the teacher to quickly check the pages which students had difficulty in understanding. The teacher could spend longer time for the explanation of suggested pages. As the results, students left more highlights and memos on the pages for better understanding of the contents. Third, the improvement of lecture strategy was conducted thanks to the real-time heat map. The teacher could reflect his lecture just after the lecture was finished and could consider new lecture plans. The improvement of the lecture was immediately conducted, and the effectiveness was clearly confirmed. In fact, many students were encouraged to put more bookmarks, highlights and memos on the pages where the teacher changed his explanation plan. We are sure that the traditional weekly or yearly feedback loops in learning analytics could not realize the immediate improvement of the lecture plan. The real-time learning analytics becomes a powerful tool to realize a real-time feedback loop, which support not only the improvement of lecture plans but also supporting teaching and learning process adaptively based on the situation in on-site classrooms.

In future works, we continue to use the proposed real-time learning analytics system for the other lectures and investigate the effectiveness in larger scale. Besides, we plan to analyze the relationship between the learning activities and learning performance of students. We also plan to develop other report graphs that support the teacher’s decisions in the classroom. Another important aspect is the qualitative evaluation how the system encourages the motivation and satisfaction of students and teachers. We are going to discuss with researchers in the cognitive and pedagogical fields and conduct further evaluation.

References


Further reading


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Mobile learning analytics in higher education: usability testing and evaluation of an app prototype

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Abstract

Purpose – The purpose of the study was to test the usability of the MyLA app prototype by its potential users. Furthermore, the Web app will be introduced in the framework of “Mobile Learning Analytics”, a cooperation project between the Cooperative State University Mannheim and University of Mannheim. The participating universities focus on the support of personalized and self-regulated learning. MyLA collects data such as learning behavior, as well as personality traits. Last but not least, the paper will contribute to the topic of learning analytics and mobile learning in higher education.

Design/methodology – For the empirical investigation, a mixed-method design was chosen. While 105 participants took part in the conducted online survey, after testing the app prototype, seven students joined an additional eye tracking study. For the quantitative part, a selected question pool from HIMATT (highly integrated model assessment technology and tools) instrument was chosen. The eye tracking investigation consisted of three tasks the participants had to solve.

Findings – The findings showed that the students assessed the idea of the app, as well as the navigation positively. Only the color scheme of the prototype was not very attractive to a noticeable amount of the participants. So, it requires slight modifications concerning the app design. For the eye tracking study, it can be stated that the students viewed the relevant parts, and they basically had no difficulties to solve the tasks.

Originality/value – Due to the empirical testing of the app prototype, the project team was able to adjust the application and to add further features. Furthermore, the backend was programmed and an additional tool (MyLA dashboard) was developed for lecturers. A mutual understanding of the targets, privacy issue and relevant features are indispensable for further development of the project.

Keywords Research, Higher education, Learning methods, Electronic media, Online applications, User studies

Paper type Research paper

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1. Introduction
The utilization of digital technologies in everyday life is constantly growing. For students, digital technologies are mostly indispensable. For example, 95 per cent of 14- to 29-year-old Germans used a smartphone in 2016 (Statista/Bitkom, 2017). However, the potential of mobile devices has not been fully developed in universities. There are numerous possibilities how digital technologies can improve learning in higher education institutions. For example, in the NMC Horizon Report 2017, six key trends were identified to adopt technologies in the higher education sector:

1. advancing cultures of learning (higher involvement in innovation development processes);
2. deeper learning approaches (connection of learning with the real world);
3. growing focus on measuring learning (analytics of data out of learning environments);
4. redesigning learning spaces (improvement of the technical infrastructure);
5. blended learning designs (combination of online and face-to-face learning); and
6. collaborative learning (social interaction and intercultural experiences) (Adams Becker et al., 2017).

The presented study covers two emerging fields of research in higher education:

1. learning analytics; and
2. mobile learning.

Learning analytics (LA) use static and dynamic information for real-time support of students’ learning processes and optimization of learning environments (Ifenthaler, 2015). Besides its flexibility, the main advantages of LA are personalization and the real-time availability of data (Ifenthaler et al., 2014). Lecturers may use rich data for pedagogical decision-making, understand individual performance development of students, identify potential lack of students’ capabilities or the need for curricular improvements (Mattingly et al., 2012). With LA, both students and lecturers can reflect on and improve their communication skills. By capturing, analyzing and visualizing the available information about learning and teaching, lecturers are able to make more reliable predictions about their students’ academic success (Macfadyen and Dawson, 2012; Mah and Ifenthaler, 2018). Furthermore, students at risk can be identified and given support through personalized pedagogical interventions (Lockyer et al., 2013). Successful applications of LA at universities are, for example, Course Signals at Purdue University, aiming to identify students at risk using an approach similar to a traffic light system (green – no risk, yellow – potential risk, red – risky). Students and lecturers can identify needs for action to improve their learning situation. Furthermore, lecturers are able to intervene and help early (Ifenthaler and Schumacher, 2016). At the University of Wollongong, SNAPP (social networks adapting pedagogical practice) is used (Dawson et al., 2011). The main purpose of this system is to increase collaborative learning. For example, conversations in forums are analyzed for investigating the relationship between students and excluded students can be determined. If students have a high learning orientation, they are discussing more frequently in forums about learning and resource sharing. And, students with a high focus on performance are discussing for example about assessments. The interaction delivers data that can be used to get an insight of student’s engagement. At the end of a lecture, the system can also be used for reflection (Sclater et al., 2016). Recent developments include LeAP (LA profiles) which provides students support toward specific learning outcomes in formal learning environments (Schön and Ifenthaler, 2018).
Mobile learning – m-learning – enables learning through personal portable electronic devices across multiple contexts (Delcker et al., 2018; Sampson et al., 2013). Through the use of mobile devices, students have access to learning artifacts more easily. The precondition is the availability of Web-connected devices. In addition, students are independent from locations, time, and they can communicate asynchronously (Lin et al., 2016). Mobile learning supports self-regulated learning (Ifenthaler and Lehmann, 2012) on the one hand, and it is an essential element of blended learning environments on the other hand (Al Saleh and Bhat, 2015). An example for a German mobile application is ARSnova of the THM University of Applied Sciences Gießen. ARS stands for an audience response system. Via this app, students and lecturers can communicate interactively. For example, students can ask questions anonymously during a lecture and the lecturer is able to answer the questions in near real time. Moreover, the communication can take place before or after a lecture. Another function is the evaluation of a lecture directly in the app (ARSnova, 2015).

The app MyLA (My Learning Analytics) of the Cooperative State University Mannheim and University of Mannheim targets to improve learning processes in higher education institutions. MyLA provides ubiquitous communication in form of short messages from students to their lecturer and vice versa. This is especially useful for dual-system courses where students are often away from the campus. Using such data, lecturers can adapt their lectures at university and implement personalized interventions, e.g. adaption of learning materials or a detailed view at topics the students have problems with. Furthermore, the app supports a more personalized and individual way of learning. The students can document their learning motivation through their learning process. The app provides information which enables students to observe their personal progress over time. In summary, MyLA combines LA and m-learning with the extension of personalized learning elements.

The remaining article focuses on the components of the MyLA app prototype and the usability testing of the app. Additionally, the current version of the MyLA app and the MyLA dashboard will be presented.

2. Literature review
Digital media and new technologies have been deployed frequently in the classroom since the 1980s. With the development of wireless internet access, innovative forms of communication and trans-regional collaboration were born. Digitalization and globalization also led to a change in higher education institutions. Particularly, the shift from traditional teaching (i.e. face-to-face teaching) to adaptive and self-regulated learning (SRL) introduced the need for smart learning classrooms. Hence, the benefits for students are a more personalized and independent learning environment (flexibility of time and location) (Hwang, 2014). According to Koper (2014), the following aspects can classify smart learning environments:

- Physical learning environments enhanced by digital devices.
- Consideration of learners’ status quo (e.g. culture, context).
- Digital devices provide additional features for learning, like virtual collaboration or communication, feedback and assessment.
- The monitoring of learners’ development using analytics results of relevant data.

Particularly interesting in this context and for generating a comprehensive understanding of students learning behavior is the use of advanced data sources. Case studies indicated that learning analytics can:
- improve the teaching quality (Ifenthaler et al., 2018a);
- support the learning engaging and motivation (Schumacher and Ifenthaler, 2018a); and
- encourage self-control (Sclater et al., 2016), as well as having potential to support assessment (Ifenthaler et al., 2018b).

The first aspect involves that a lecture can adapt the curriculum toward the students’ requirements. As a predictive tool, LA can help to enhance the students’ retention. Furthermore, the learners can use the tracked, analyzed and often visualized data as a self-control mechanism.

A current study investigated three relevant features of LA from the students’ point of view (Schumacher and Ifenthaler, 2018b):
- Possibility of self-assessment.
- Recommendations for learning.
- Timeline for the evaluation of the students’ status quo.

Moreover, privacy is an important aspect when it comes to LA. Students recommend clear transparency and trustfulness of LA applications (Ifenthaler and Tracey, 2016). By providing the users with access to and control over their personal data, confidence can be enhanced (Prinsloo and Slade, 2015). One further aspect is the possibility of making an interpretation of the learners’ information very simple. By visualization of the data, learners, lecturers, as well as other stakeholders can easily identify a good or poor performer (Ebner et al., 2015). Furthermore, individual information can be collected from different sources. While login information and the frequency of particular websites are classically representing quantitative data sources, entries in forums or blog, for example, have to be interpreted as qualitative resources (Ifenthaler and Schumacher, 2016).

Dashboards including vast amounts of data, for example, performance or user data, are a technical solution to support the teaching and learning process. The majority of dashboards used in the context of learning and teaching consider four stages. First, teachers are getting aware of several activities (e.g. the use of learning materials) in the course by using a dashboard. Next, they can reflect concerning their actual teaching process under consideration of the collected data. As a third step, teachers can identify at-risk students or isolated ones more easily. Last but not least, dashboards can be used to become aware of the current impact, and thereby how the information can help to support the students, e.g. through proving opportunities for re-socialization or providing feedback to poor performers (Verbert et al., 2013).

Usability testing for mobile applications considers different factors. For example, Nielsen (1993) mentioned five attributes: learnability, efficiency, memorability, errors and satisfaction. Learnability covers an easy-to-learn approach, efficiency leads to high productivity, memorability helps to remember the system more easily, errors should not occur or can be revoked and satisfaction means that users like the system. But there are more attributes that can be valuable for usability testing. As an example, the MAUEM (mobile application usability evaluation metrics) model has nine attributes. The five of Nielsen and four added attributes: effectiveness, cognitive workload, interruptability and simplicity (Saleh et al., 2017).

A usability example will be introduced of ME2.0 (Mobile Electronic Personality version 2). This is an application that helps users to manage their personalization attributes, e.g. against identity thefts. The methodology covered two studies. In the first study, users (N = 9) read different scenario uses of the application before they were interviewed. In a last step, the
participants illustrated their own desired UI and navigation. The second study consisted of an online survey ($N = 16$) and an evaluation of an illustrated prototype ($N = 4$) (Oyomno et al., 2013). Another example is EASEL (Education through Application-Supported Experiential Learning). This is a mobile platform, which can be used by instructors to send reflection, as well as content prompts. After a pre-conducted needs analysis, a prototype was built. The participants ($N = 14$) were divided in faculty members ($N = 8$) and students ($N = 6$). Each group had to solve similar (but different) tasks toward a hypothetical scenario. The screen was recorded for analyzing how participants navigated within the application, and the facilitator observed them. All participants were asked to “talk-aloud” while completing the tasks. For documenting comments or gestures, cameras were used to record all sessions. After each task, the participants answered short questionnaires about their experiences. Furthermore, the usability questionnaire was conducted with questions concerning their general use of technology and application-related questions. In addition, all participants were asked to discuss their own experiences with the facilitator (Schnepp and Rogers, 2017).

3. Usability testing
This section focuses on the methodology, as well as on the findings of MyLA prototype’s usability testing. This is the basis for the actual app and the additional MyLA dashboard, which will be introduced in Section 4.

3.1 App prototype
The Web app prototype of MyLA consists of three different main units (see Figure 1):

1. My Profile;
2. My Learning; and

The general page structure consists of the following:

![Figure 1. Web app prototype MyLA (translated from German; state April, 2017; own figure)]
My Profile contains two subcategories:
(1) profile data with input options like username or university; and
(2) the trophy center where app users have access to their rewards, i.e. when entering the profile data or participating on a certain questionnaire. This section includes administrative information of every app user.

My Learning contains two subcategories:
(1) the pinboard where students can create posts for their lecturers; and
(2) the survey center where students can respond to regular conducted questionnaires. Within this section of the app, the students can communicate with their lecturers and vice versa. Via pinboard, students can post messages by using tags (e.g. ask questions or point to a problem). This will be only visible for the responsible lecturer on their dashboard interface.

My Progress contains two subcategories:
(1) MyLA data where students can enter personal data like learning motivation or learning effort; and
(2) MyLA stats where the MyLA data will be visualized in charts. This part displays the individual progress in additional (learning) factors.

The design of the app was realized to accommodate the corporate design of the Cooperative State University Mannheim and University of Mannheim. Therefore, one significant color of each education institute had been extracted. As a next step, the colors were combined and supplemented by neutral colors.

According to the approach of LA, the first prototype of the MyLA app was designed to capture user data. Further steps will be collecting the data reports and deriving individual actions for students. Thereby, the main objective of developing personalized and adapted learning environments will be striven. The current app version has been modified and adapted. Additionally, a dashboard for lecturers has been developed.

3.2 Research questions
The usability testing focused on three major research questions:

RQ1. How intuitive is the MyLA prototype (design, navigation) for students?

RQ2. Is there room for improvement for the development of the MyLA prototype?

RQ3. How can the empirical results (quantitative and qualitative) help to optimize the MyLA prototype for its initial implementation?
The questionnaire was conducted to evaluate design, navigation, text elements and used icons of MyLA. Beforehand, the students were shortly introduced to the topic of LA. Afterward, they were able to view the MyLA app either on web browser (Cooperative State University Mannheim) or on mobile browser (University of Mannheim), and afterward responded to an online questionnaire. For the purpose of comparability, none of the participants has used the MyLA Web app before.

3.3 Methodology

3.3.1 Participants. The usability test was conducted with $N = 105$ students ($N_1 = 56$ Cooperative State University Mannheim, $N_2 = 49$ University of Mannheim; 51 female, 54 male) in April 2017. The average age of the participants was 23.65 years ($SD = 3.72$, Min = 19, Max = 35). The majority of the respondents ($N = 99$) were studying in the field of business administration. More than half of the students were enrolled in a bachelors program (53 per cent) and 47 per cent were studying in a master’s program. In addition, seven students (four female, three male) took part in an additional eye tracking study. On an average, participants reported that they are spending 29 days ($M = 28.90$, $SD = 4.56$) per month with apps generally, but only four days per month ($M = 3.65$, $SD = 6.06$) with apps for learning.

3.3.2 Design and procedure. The usability test was divided into two parts using a standardized instrument (see Section 3.3.3): First, the participants made themselves familiar with the MyLA app prototype via web browser or mobile browser. This included the navigation through the app and reviewing the design and the app’s structure. Second, they responded to an online questionnaire which was structured as follows: Socio-demographic information, general usage of mobile devices and technologies, and MyLA-specific questions (open and closed questions). MyLA-specific questions focused on navigation and navigation elements, design and app structure. The main group ($N = 98$) followed this procedure. A smaller group ($N = 7$) participated in an eye tracking study (see Section 3.3.4).

A significant difference between the participants was the device on which MyLA was tested: One group (Cooperative State University Mannheim) tested on a web browser via a personal computer and another group (University of Mannheim) on a mobile browser via a tablet. To ensure anonymity, various identification numbers had been given to the students.

3.3.3 Usability instrument. The feedback of the students was committed via an online questionnaire. The question pool within the MyLA-specific part was chosen following the usability testing instrument developed for HIMATT (highly integrated model assessment technology and tools). The instrument has been successfully tested for reliability and validity (Pirnay-Dummer et al., 2010). For the MyLA usability testing, 13 items had been chosen. To give an example, one item was: “I found it easy to navigate through the software”. All questions were answered on a five-point Likert scale ranging from highly agree (5) to highly disagree (1). Figure 2 shows the 13 items used in the usability testing.

3.3.4 Eye tracking. According to Rayner (2009), eye movements are connected to a participant’s attention, and can therefore contribute to the usability testing of screen-based applications. Eye tracking is a standard methodology to record the eye movement of participants. The data evaluation is conducted with special eye tracking software. A very useful feature is the report function that visualizes the eye movements through heat maps or gaze plots (Kurzhals et al., 2017). Common observations in eye tracking studies include (Ehmke and Wilson, 2007):

- fixation points: where participants have a long look;
- first look: where participants look first; and
- non-looking: elements participants do not pay attention to.
After a short introduction, the students were instructed to solve three tasks by using the app prototype. The difficulty of each task was ascending. Therefore, seven AOI (areas of interests) were defined for the analysis with Tobii Pro Studio software. All participants were recorded with regard to their “first look” and on which MyLA contents they looked more often (“fixation points”). Furthermore, the student’s solution approach was analyzed. The topics of the three tasks can be summarized as follows:

1. Calling the Cooperative State University Mannheim website as soon as possible.
2. Selecting and saving their respective university in the subcategory profile data.
3. Creating a post for a lecturer.

Students from the eye tracking study also participated in the survey-based usability test.

3.4 Results
The presentation of findings is divided into the survey-based and eye tracking usability test. Data analysis was conducted using IBM SPSS 23.0 and Tobii Pro Studio.

3.4.1 Survey-based usability test. The main part of the questionnaire was to investigate the app’s navigation and design. Figure 2 shows the findings of the 13 items from the survey-based usability test.

The bar charts in Figure 2 are divided into two sections. The chart on left side shows the results concerning the navigation and structure of the MyLA prototype. The second chart on right side highlights the outcomes regarding the design and colors of MyLA. According to the navigation and structure, it is conspicuous that all six average values are constantly high. The highest value was reported for the simplicity of MyLA app prototype with an average of 4.45 (SD = 0.83). Followed by “I found it easy to navigate through the app” (M = 4.36, SD = 0.82) and “The navigation of the app is user-friendly” (M = 4.28, SD = 0.85). Based on the second chart, it is obvious that there were some divergent opinions concerning the design and colors of MyLA. The lowest rated value was the use of color with an average of 3.28 (SD = 1.15). In addition, the participants ranked the design of MyLA as “optically appealing” with 3.36 (SD = 1.19).
3.4.2 Eye tracking usability test. For the purpose of statistical analysis, either the time of first fixation or the time to first mouse click were calculated. Table I shows the average times the pilot tester (conducted by a research team member) and the participants needed to complete the three tasks. The eye tracking study was implemented using the web browser version of MyLA (on a personal computer).

Table I shows that the majority of the participants (at least five) were able to solve the simulated tasks. For task three, the students needed more time to find the solution in comparison to the first two tasks when compared to the benchmark of the pilot test. A possible explanation may be an unclear description of the task. Some students were not able to find the pinboard on a direct way (via chapter icon “My Learning”). However, all participants completed task three through an alternative solution (via side navigation menu).

As a next step, a heat map analysis was conducted which is a reflection of the screen where the participants viewed longer than other parts (Ehmke and Wilson, 2007), identifying gaze behavior precisely (Duchwoski et al., 2012). Through the accumulation of all single viewpoints of a participant, the fixation points can be highlighted. Figure 3 shows the accumulation of the fixation points recorded by all participants. The viewpoints were predominantly recorded on the left side of MyLA prototype. For solving task one (pictured in the heat map of Figure 3), the participants had to look at the left side to find the Cooperative State University Mannheim logo. Additionally, it has to be considered that the participants saw the app via a desktop browser; hence, the screen width was obviously wider than on a mobile device.

<table>
<thead>
<tr>
<th>Tasks</th>
<th>Pilot test (N = 1)</th>
<th>Participants (N = 7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>01 – Website challenge (click on a logo)</td>
<td>1.91</td>
<td>M = 4.86, SD = 2.46 (solved by 5 of 7)</td>
</tr>
<tr>
<td>02 – University selection (in the profile)</td>
<td>10.09</td>
<td>M = 14.55, SD = 9.43 (solved by 5 of 7)</td>
</tr>
<tr>
<td>03 – Pinboard post (create a new one)</td>
<td>4.81</td>
<td>M = 10.12, SD = 9.02 (solved by 7 of 7)</td>
</tr>
</tbody>
</table>

Figure 3. Heat map showing the cumulated fixation points of all eye tracking participants (exported using Tobii software)
4. MyLA app and MyLA dashboard
In this section, the current applications (MyLA app and MyLA dashboard) will be introduced. The navigation and design were adjusted on basis of the conducted usability testing in spring 2017.

4.1 MyLA app
The app prototype of MyLA has been extended and modified in functions and design. While the app prototype was already assessed as “intuitive” and clear in its navigation, only the color scheme was modified. By realizing app version 1.0, this issue was fixed and a more reduced, neutral and clear color scheme was implemented. The three main categories My Profile, My Learning and My Progress are still the same as in MyLA’s prototype. Besides the style adjustments of MyLA, the backend infrastructure has been developed. And because MyLA app is primary for students, there was an additional need to create an additional surface for lecturers. Therefore, the MyLA dashboard has been developed in line to the MyLA app. The current app version 1.1 (February 2018) has come up with some slide modifications. Students can receive lecture messages, published only to this lecture (compare to Pinboard Entries in the next section). Moreover, the app user can see what is new in the app via a notification bar, added on top of the footer. The number of notifications is also shown near the home button. Furthermore, it is visible in the side menu and on the app’s homepage partitioned by category and subcategory. Additionally, general statistics of the app user can be accessed via the site app statistics. For example, users can see their registration date or the total number of submitted pinboard entries.

Figure 4 shows a screenshot of the MyLA app’s homepage consisting of three links (top-down: My Profile, My Learning, My Learning Progress) to all three categories, mentioned...
4.2 MyLA dashboard

The dashboard version 1.1 has identical functionalities and navigation parts as the application. The dashboard’s homepage contains: Pinboard Entries, Survey Center and LectureTracker. The connection between both applications is managed via profile settings. The instructor has to register a certain lecture and define an access code. This code and the automatically given lecture number are requisites for joining one particular virtual lecture. Via Pinboard Entries lecturers can receive messages, answer them or mark them as read. Additionally, he or she can filter the entries regarding several tags (e.g. question or problem). Furthermore, instructors are capable to send lecture messages consisting texts and optional links and files. Via the feature Survey Center, lecturers have the possibility to create surveys using existent questions or adding own questions. Because of the LectureTracker, instructors can observe the aggregated MyTracker values of the students. There are three options to filter the data: on a daily, weekly or monthly level. The dashboard is only managed by the lecturer to start an action (e.g. new survey), react on students’ action (e.g. comment pinboard entry) or observe students’ progress (e.g. LectureTracker).

Figure 5 shows a screenshot of the MyLA dashboard’s homepage consisting of three grids with all parts and functionalities, mentioned above. On the left side are the Pinboard Entries (“Pinnwand-Einträge”) and also a collapsible unit to submit a message to the respective lecture (“Kursnachricht erstellen”). In the middle grid, the Survey Center (“Umfrage-Center”) is visible. The two collapsible units display a series of default questions (“Übersicht Fragen-Pool”) and a form to submit own questions with own options (“Eigene Frage zum Pool hinzufügen”). On the right side, instructors can observe the aggregated values of the whole lecture using the LectureTracker (“KursTracker”). All MyTracker data, which will be reported by students, result in the average values. Furthermore, above the...
dashboard’s footer, the notification bar is visible identically to the MyLA app. The header contains several buttons like: profile, reload and options button (with e.g. imprint and privacy).

5. Discussion and conclusion
Usability testing is a very useful and advantageous method for formative evaluation of the development process (Pirnay-Dummer et al., 2010). The project MyLA can benefit from the valuable input of the potential app user.

With regard to $RQ1$ (“How intuitive is the MyLA prototype (design, navigation) for students?”), it can be suggested that the prototype is intuitive for the target group. Overall, the results were predominantly positive (all average values were higher than 3); however, some issues were identified for improvement, especially with regard to colors.

In addition, students provided feedback within the scope of open questions. The students evaluated the app’s clarity, simplicity, navigation/structure and features as very positive. Regarding the assessment of the color scheme, the responses were heterogeneous. Critical issues were partly used dark colors, as well as color combinations. Moreover, some students mentioned that the app contained a broad color spectrum. Furthermore, they suggested additional features for future app versions, e.g. a calendar function. With regard to $RQ2$ (“Is there room for improvement for the development of MyLA prototype?”), it can be summarized that the colors need to be adjusted.

To answer the $RQ3$ (“How can the empirical results (quantitative and qualitative) help to optimize the MyLA prototype for the main survey?”), the following aspects can be summarized. The involvement of the target group (students) was very important at this early project stage. The reason for that is very simple, because the students are prospective users of MyLA. Therefore, it is inevitable to get them highly involved. The success of a project depends on its acceptance. If the acceptance is high, the potential usage can be high, too. For reaching a large consumption of MyLA, it is necessary to implement the students’ feedback and recommendations. With help of these new insights, future adaptions can be managed. Hence, the findings of the MyLA usability testing provided detailed insights to optimize the app prototype. Some lessons learned of the MyLA usability testing were the following proven statements:

- The handling of the MyLA Web app prototype is intuitive.
- The app’s structure is easy to learn.
- The navigation within the app is clear and user-friendly.
- The students mostly like the idea of MyLA.
- The design and colors can be improved, because the opinions deviate fairly high.

With respect to the usability testing and the students’ recommendations, the app was adjusted. Furthermore, an additional application for lecturers was developed (MyLA dashboard). For guaranteeing the functionality of both tools, they were tested with a small sample. One aim of the research project is to focus on the needs of the major target groups (students and lecturers); thus, several workshops were conducted in 2017 and further events are planned for 2018. With respect to the current status of the project, it has to be mentioned that the panel study started successfully at the beginning of 2018. First prefunded results of the study will be available in summer 2018.

MyLA can be used in different learning settings like in lectures, workshops or practical phases. The lecturer can integrate both applications as they fit his/her needs the best. There are no universal approaches, but it is highly recommended to clarify the general setup
of using MyLA to the students in an early process stage. The applications can be used for student feedback, communication with the lecturer, (flexible) time management and for performance or lecture evaluations. Via the MyLA dashboard, the lecturer can manage these functionalities and observe the incoming data. Additionally, the identification of further functionalities needed by the students is an evident part of the project.

According to the literature, the research area of LA is still in its infancy in German-speaking countries (Ifenthaler and Drachsler, 2018; Ifenthaler and Schumacher, 2016). Moreover, with the advance of digital technologies, new skills and competencies are required from students and teachers in higher education institutions, as well as their future workplace (Gibson and Ifenthaler, 2017). In addition, the situation of non-traditional academics will be considered within the project. The combination of LA and m-learning seems to be beneficial to contribute to the individual demands of a diverse group of learners. For example, the project team aims to identify patterns of learning behavior and the management of learning tasks, given a high demand of workload at the university and the workplace (Ifenthaler, 2018). In summary, the project can be seen as an important contribution to the topic of LA for higher education in Germany.

Some limitations and challenges of MyLA (and probably other applications) are as follows:

- Re-designing and implementation of digital tools in curricula.
- Conviction of lecturers to sustainably use digital offers.
- Boost of m-learning concepts in higher education.

Some chances of MyLA are as follows:

- Data collection concerning application usage for research improvement in Germany.
- Privacy-based approach.
- Data collection for lecturers to identify certain problems within a lecture.
- Transfer the Web app to a hybrid app for using device capabilities in future.

As a conclusion of all mentioned points above, there is more research necessary. Some useful research approaches could be: how should a privacy-based application look like in the opinion of students and lecturers, what are overlapping interests of students and lecturers to strengthen and adapt app functions or digital innovations, how can different digital approaches (in one university or cross-university) work together to not “reinvent the wheel”. Furthermore, as already discussed, the additional app features have to be implemented in case of further development. All in all, the project delivers a profound base with many important research questions and approaches for future work.

References


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Using mobile devices to support cognitive apprenticeship in clinical nursing practice – a case study

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Abstract
Purpose – This paper aims to illustrate how mobile devices could be applied to substantiate cognitive apprenticeship model to optimize nursing students’ learning experiences in clinical settings.

Design/methodology/approach – Eight female students from a nursing college in Taiwan were recruited in this study. They enrolled in a three-week nursing clinical practicum session in the area of psychiatric nursing.

Findings – Analysis of interview data from students and instructor showed that use of the mobile technology could promote the effectiveness of cognitive apprenticeship model, especially for processes of reflection, coaching, scaffolding and articulation.

Originality/value – The present study intended to bridge the gap between mobile technologies and cognitive apprenticeship. This study explored students’ experiences and expectations of using mobile technology in clinical nursing courses and clarified how the cognitive apprenticeship model fits students’ experiences during using mobile technology in the clinical nursing course.

Keywords Mobile technology, Clinical nursing practice, Cognitive apprenticeship model

Paper type Case study

Introduction
Cognitive apprenticeship has been popularly used in nursing education during the 2000s because of its emphasis on social-constructivist methods of supporting learning (Austin, 2009; Poitras and Poitras, 2011; Woolley and Jarvis, 2007). With the rising of mobile technology, research about integrating mobile device into cognitive apprenticeship has been conducted in diverse fields such as mathematics education, computer science learning, educational games design, environmental education and history learning (Chang et al., 2013; Chen and Chen, 2014; Klopfer and Squire, 2008; Ma et al., 2008; Wu et al., 2009). However, there are few practical cases regarding using mobile devices to support cognitive apprenticeship in nursing education; studies conducted to describe nursing students’ views regarding the use of mobile technology in cognitive apprenticeship are even fewer. The present study intended to bridge the gap between mobile technologies and cognitive apprenticeship. This study explored students’ experiences and expectations of using mobile technology in clinical nursing courses and clarified how the cognitive apprenticeship model fits students’ experiences during using mobile technology in the clinical nursing course.
Background
In diverse ways, the intensifying complexity of patient health issues and the rapid expansion of knowledge underlying practice have been building momentum for change in nursing education (Billings et al., 2012). One of the emerging trends in nursing education is to integrate the mobile technology into nursing curricula.

Over time, the incorporation of emerging technology into clinical areas has demonstrated its potential to provide more student learning opportunities, create innovative teaching practices and promote current, accurate information retrieval systems for nursing care (Jeffries, 2005; Day-Black and Merrill, 2015). From the literature review for research articles pertaining to mobile device use in nursing education, Doyle et al. (2014) listed the following advantages of using mobile devices in nursing education:

- saving time to access information resources;
- improving student learning;
- increasing student self-efficacy;
- decreasing clinical information stress; and
- decreasing student cognitive load.

Furthermore, mobile devices were also useful in improving patient safety, promoting the quality of care and increasing student confidence (Johansson et al., 2013; Johansson et al., 2014).

Though the use of mobile device in nursing practice can be traced back to early 2000s, mobile device was unable to be a prominent tool in nursing practice at that time because of the low penetration rate and the lack of dedicated apps. While the rate of adoption of mobile devices has increased, the role of mobile device in education is undergoing rapid evolution. The use of mobile learning has progressed from focusing on the nature of mobile devices to mobility of the technology and now the emphasis is the mobility of the learner and the learning process (Traxler, 2007; Mackay et al., 2017). In the field of nursing education, however, participants used mobile devices primarily as reference tools, but less frequently as tools for reflection, assessment or cooperation during the clinical practicum (Strandell-Laine et al., 2015; Lai and Wu, 2016). In other words, more structured assignments and activities designed to encourage the implementation of mobile devices were needed (Johansson et al., 2014; Raman, 2015).

Doyle et al. (2014) suggested that “educators who are planning to incorporate mobile devices into the curriculum may benefit from the application of a theoretical framework to support implementation”. Two areas of theories and models currently used when investigating technology are technology adoption and implementation science. Technology adoption focuses mainly on how the end users adopt technology, whereas implementation science describes methods, interventions and variables that promote the use of evidence-based practice (Sharples et al., 2005). Based on cognitive apprenticeship model, the present study tried to propose a framework that mobile devices could be applied to substantiate cognitive apprenticeship model to optimize clinical learning experiences. Mobile device adoption and implementation science in each method of cognitive apprenticeship model were described in detail.

Cognitive apprenticeship model
While using mobile technology to assist practice training has been becoming an important and popular discussion topic in nursing education, apprenticeship model, on the other hand, has long been used in nursing education for clinical training. The drawback of traditional...
Clinical training is that learning is driven by the day-to-day demands of the workplace where learning opportunities and supervision do not have first priority (Collins et al., 1989; Dornan, 2006; Taylor and Care, 1999). In contrast to traditional apprenticeship, the cognitive apprenticeship takes a more deliberate approach to promote the development of cognitive skills (Chen et al., 2015), emphasizes that the thinking must precede and be part of the task and needs to deliberately bring the thinking to the surface to make it visible. Cope et al. (2000) discovered that the explicit use of mentoring techniques derived from cognitive apprenticeship is helpful to student nurses’ learning. The course infrastructure and instructional strategies that draw upon cognitive apprenticeship model had many benefits to baccalaureate nursing students such as encouraging participation and interaction; fostering peer coaching, collaboration and consultation; and improving cognitive and clinical reasoning skills (DeBourgh, 2001). The cognitive apprenticeship model was useful for teaching strategies in undergraduate clinical training and a valuable basis for evaluation, feedback, self-assessment and faculty development of clinical teachers (Stalmeijer et al., 2009).

Cognitive apprenticeship, as described by Collins et al. (1991), is “a model of instruction that works to make thinking visible”. To substantiate the cognitive apprenticeship as an effective instructional model, Collins et al. (1989) proposed six methods to support learning: modeling, coaching, scaffolding, articulation, reflection and exploration. As Figure 1 shows, the six methods break down into three groups.

The first group, including modeling, coaching and scaffolding, represents the core and is designed to help students acquire an integrated set of cognitive and meta-cognitive skills through observation and supported practice.

**Modeling**
The modeling component involves the expert performing a task so that the learner can observe and build a conceptual model of the processes required to accomplish it. For novices in psychology nursing, developing therapeutic communication skill is the first step.

**Coaching**
The coaching phase entails observing students perform a task and offering specific guidance or assistance to help them bring their performance to a higher level of expertise.
Scaffolding
Scaffolding includes any of the supports provided to students before or during a task. It may involve simple interventions such as hints, directions and reminders. It may also involve more complex planning, such as breaking a task down into component parts that students can more easily achieve or performing a part of a task so that students can assume as much of the task as possible.

The second group, articulation and reflection, is designed to focus students’ observations of expert problem-solving and to gain control of their own problem-solving strategies.

Articulation
Articulation encourages students to describe their knowledge, reasoning or thinking processes. Once articulated, knowledge and thinking processes can be observed, understood, shared or elaborated through dialogue with teachers or their peers.

Reflection
Reflection requires the expert/teacher to direct and encourage the student to analyze and be critical of their performance/experience. The use of journal writing as a means of promoting reflection and learning in educational settings has been widely advocated in health-related courses in an effort to enhance self-awareness, interpersonal understanding, critical analysis, cognitive learning and clinical reasoning skills (Chirema, 2007).

The final group, exploration, is intended to encourage learner autonomy and problem formulation by the self (Chee, 1995). This involves pushing students to actively manipulate and explore the nursing skills or knowledge to solve real practice problems on their own.

Initially, the student learns by watching the teacher model expert-level practices or strategies for learners. The internal processes that the teacher goes through must be articulated so students have access to the various internal strategies and heuristics that are used by the teacher (Collins, 2006). The teacher provides “scaffolds” which will support learners in their attempt to participate in expert practices or strategies. The teacher also coaches the students by offering guidance and feedback in the student’s learning process. While students are adopting and learning new practices, they are strongly encouraged to reflect on their experiences and articulate their reasoning in using various strategies and practices. Learners are also provided with opportunities for exploration to enable them to apply some of the cognitive processes they have developed to new challenges (Collins, 2006).

There have been studies on the integration of modern technology and cognitive apprenticeship methods in nursing education (Chen et al., 2008; DeBourgh, 2001; Ranson et al., 2007; Woolley and Jarvis, 2007). However, few studies focus on the use of mobile technologies in support of cognitive apprenticeship and even fewer focus on exploring students’ experiences regarding how mobile technologies improve the cognitive apprenticeship model during clinical training. Previous studies either implemented non-mobile technology or focused on the learning improvement of participants. This study aimed to enrich the studies in this field and achieve the following purposes. First, this study presents how to incorporate the convenience of a mobile learning environment model’s framework during nursing clinical training. Second, this study investigates the effects of integration of a mobile learning environment in support of cognitive apprenticeship model in a clinical setting. Finally, this study theorizes about the impact this integration might have on learners’ perceptions about technology integration for their future clinical practice.
Method

Participants and settings

Eight fourth-grade students from a five-year nursing college in Taiwan were recruited for this study. The students were all female, with average age of 19.2 years. They enrolled in a three-week nursing clinical practicum session in the area of psychiatric nursing. Prior to the practicum session, students had taken the “psychiatric nursing” course but did not have clinical experience. Students also completed clinical practicum courses such as fundamental nursing, medical and surgical nursing, obstetric nursing, pediatric nursing and community health nursing prior to enrolling practicum. These students were supervised by an instructor and each was provided a mobile device throughout the practicum. In each practicum session, the school usually arranges six to eight students in one nursing unit. The clinical setting in this study was a private middle-sized mental hospital located in central Taiwan.

Applying cognitive apprenticeship principles

An experienced nursing teacher (i.e. the instructor) was recruited to help develop and field-test the constructed mobile-based cognitive apprenticeship learning environment. Through observation of the teacher’s training sessions and discussions with the teacher, functionalities of the mobile learning environment were identified. The mobile-based cognitive apprenticeship environment was then designed to foster a three-week nursing clinical practicum session.

Based on the characteristics of this study, the technical literacy of participants has a great impact on the research results. Evidence from some studies indicates that nursing students and educator staff were lacking technology literacy (Bond and Procter, 2009; Button et al., 2014; Maag, 2006; Wu and Lai, 2009; Wu and Sung, 2014; Wyatt et al., 2010). The course instructor and students were required to participate in a training session on using mobile device and apps before the experiment.

The practicum session was conducted to provide students with clinical experiences in the area of psychiatric nursing. During the practicum, each student was assigned a patient to take care to progress through four steps of nursing process, including assessing patient’s problem, developing nursing plan, implementing nursing plan and evaluating nursing outcome. For students, assessing patient’s problem is the first and most difficult part because this involves effective communication, problem-solving and decision-making skills. Next, we describe how the mobile-based learning was integrated with cognitive apprenticeship model to support the clinical teaching and learning.

- Modeling. Two learning tools were used to foster students’ learning in this activity. First, a demo video that illustrates communication skills with mental patients performed by expert practitioners was put into students’ mobile devices, which allows them to access anytime and anywhere. In turn, this facilitates the pre-loading of essential content that helps them begin to develop a conceptual model of the processes required, and a frame of reference for the activities they are to watch and learn. Subsequently, during the clinical session in the hospital, this was augmented on the spot by the teacher/expert demonstrating the communication process involved while giving explanations and reasons why it was performed that way. At the same time, students used voice recorder app to record the verbal communication between the instructor and them (the students acted as the patients) to further analyze the tacit knowledge to help their development of the cognitive processes that underpin problem-solving.
Coaching. In the psychiatric nursing practicum, students’ primary daily activities in the hospital included attending to the hospital’s morning report, practicing morning care and routine nursing, participating in patients’ team therapeutics and participating in a discussion session held by the instructor. To help students perform these activities, students were asked to submit all of their assignments such as reflective journal, nursing recording, nursing assessment and communication analysis to the course server via their mobile devices. And the instructor would coach students online by providing hints, feedback and reminders to assist them to perform closer to their own level of accomplishment.

Scaffolding. Several evaluating apps which offer measurement scales and operation hints were designed to help students develop observation and recording intelligence. With these apps, students conducted mental patients’ observation and completed their recording tasks. The observation records were sent back to course server synchronously and the instructor would realize each student’s achieved percentage of scheduled progress. Scaffolding is coupled with fading, the gradual removal of the expert’s support, as students learn to manage more of the task on their own. Therefore, once the students made progress in observation or recording tasks, they would be increasingly independent of these tools.

Articulation. Three mechanisms were used to facilitate this process in our study. First, a discussion forum was created. Students could either respond to the instructor’s postings or initiate their own topics of interest via mobile device or PC. The nurse mentors were also invited to join in the discussions where ideas and experiences from the field could be shared. Second, on the spot, the mobile device also supports articulation process by providing a visual presentation app to facilitate their daily meeting session, in which whatever happened in one day was discussed. Finally, students could use mobile device to refer other students’ assignments to compare those with theirs.

Reflection. To promote this process, a reflective journal app was designed. Students were asked to briefly describe the setting and their thoughts and choose some items which best expressed their mood to reflect on their attitudes, feelings and cognitive dimensions of learning. After students finished their journals in the hospital, they immediately submitted them to the instructor. And the instructor would provide them encouragement or guidance by asking reflective type questions such as “How do you feel that went?” or “Why did you choose to do it that way?”. With the reflective journals, the instructor could know students’ conditions promptly and provide them with timely feedback, which was just not possible with the previous paper-written journal.

Exploration. To facilitate the process, a concept-mapping app was provided for them to draw the relationship of patients’ various problems. This process stimulates students to evaluate what they understand and what they still need to learn. Clinical concept mapping promotes critical thinking and prepares students for clinical experiences by helping them organize complex patient data, process complex relationships and encourage holistic visualization of the patient (Baugh and Mellott, 1998). Furthermore, many related resources were collected and saved on the mobile device to provide students quick access to refer and identify patients’ problems.
Data collection and analysis
To better understand the pragmatics, suitability, affordances and constraints of integrating mobile technology in supporting cognitive apprenticeship methods in a clinical nursing course, one goal of this study was to present students’ reports of how mobile technology impacted their learning process in each method of cognitive apprenticeship. In other words, with these reports, we can more specifically understand the practical situation in which students interact with mobile technology, how the cognitive apprenticeship model functioned in the mobile-based learning environment and what are the benefits and/or difficulties encountered by students in this learning environment. To yield more varied results than individual interviews (Barbour, 2005), this study used focus groups to explore students’ perceptions and ideas about the use of mobile technology in supporting cognitive apprenticeship methods. Students were divided into four groups and each group had two students.

Two students were included in each focus group in this study for the following two reasons. First, students work in pairs during their nursing practice. Considering the heavy load of work on them, it is convenient to use their common leisure time to hold group interview. Second, as each student shares the same working experience with their partner and was familiar with each other, it is easier for them to speak openly in interview. In qualitative research, the number of participants depends upon the number required to inform fully important elements of the phenomenon being studied (Sargeant, 2012). In this study, participants are all classmate friends and they have ample opportunity for informal exchange of experience and opinions with each other by using the apps we provided. Hence, it is reasonable to say that the focus group findings may be representative of an entire population.

To deeply understand students’ and teachers’ opinions about using mobile device in each element of cognitive apprenticeship, a semi-structured interview was conducted. Interview guidelines with open-ended questions and guided statements were established. These questions were designed based on the topics shown in Table I. For example, in modeling

<table>
<thead>
<tr>
<th>Cognitive apprenticeship teaching methods</th>
<th>Instantiation in the mobile-based learning environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modeling</td>
<td>A video that illustrates experts’ communication skills with psychiatric patients was put into students’ mobile device Students used mobile device to record the instructor’s verbal communication with them</td>
</tr>
<tr>
<td>Coaching</td>
<td>Students used mobile device to submit their assignments and the instructor coached them online</td>
</tr>
<tr>
<td>Scaffolding</td>
<td>Nursing assessment and recording tools were designed into mobile device to scaffold students</td>
</tr>
<tr>
<td>Articulation</td>
<td>Students participated in the discussion forum moderated by the instructor The instructor and students used mobile device to have the daily meeting Students shared the assignments each other</td>
</tr>
<tr>
<td>Reflection</td>
<td>Students used mobile device to write daily reflection journal</td>
</tr>
<tr>
<td>Exploration</td>
<td>Students used concept-mapping app to draw clinical concept map Students used mobile device to refer related nursing resource</td>
</tr>
</tbody>
</table>

Table I. Cognitive apprenticeship teaching methods in mobile learning environment
method, the students were asked questions such as “Did you use mobile devices to record the instructor’s demonstration? Why? Each interview took 20 to 30 min and was audio recorded. On the completion of each interview, data were transcribed in detail. According to each application of mobile device in cognitive apprenticeship model, a content analysis method was used to analyze the data. Those contents with similar implementation were then grouped into the same category. Finally, arguments in support of various applications were justified. To further verify students’ opinions about the effect of each application, the instructor was interviewed by the researcher (i.e. the first author) after compiled students’ arguments. The interview questions were designed according to students’ perceptions and our premise that cognitive apprenticeship can be improved when it is supported by a mobile-based learning environment. A sample question was:

Q1. One of the students did not think that the videos or recordings in mobile devices were very helpful to their learning. What did you think and why did you think that?

Result and discussion
This study has set out a mobile-based learning environment to support the implementation of cognitive apprenticeship in clinical nursing education. In the following sections, students’ and the instructor’s perspectives on the effects of using mobile device in support of each element of cognitive apprenticeship were described.

Mobile device helps record the modeling process
In the modeling process, students were encouraged to use mobile device to record the talk while the instructor demonstrated the communication skill in the hospital. The analysis of interview data revealed that most of students said that they had used mobile device to record the instructor’s demonstrations and thought it was particularly helpful to their talk with patients. Student #1 stated that:

Watching instructor’s demonstration, we figured out the key point of communication with the patient and learned how to talk with patients and guide them. We’ve learned how to have deep conversation with patients rather than shallow talk that leads us to nowhere with them. We would involve some emotional problems.

However, just one student (student #1) said the video was good for her learning. The instructor made similar comments on the video for her learning. She admitted that the video on the mobile device was demonstrations of general communication skills, but the mimic conversations with students on the scene did not reflect the real problems which students encountered on the instant. “Therefore, students were very impressed by it”, the instructor said.

Mobile device facilitates the process of coaching and scaffolding
The mobile-based coaching and scaffolding was the second effective course element which students expressed. Notably, they found value in observing and assessing patients’ physical and mental states. Students’ feedback included:

Student #3: The whole design actually helped us a lot, which was not the same as our previous practicum in which we had to grope for the direction by ourselves. This time those tools helped us make observations on the patients’ mental states and symptoms. For example, the Scale for the
Assessment of Negative (Positive) Symptoms provided us with the guidance of what to observe the patients and then how to collect the data.

Student #4: When you conducted the assessment tasks, you should first find out some data of the patients. Without the reminder from those tools, you might not have in mind for what kind of data.

Student #5: Our assessment skills were promoted after we used those tools because those tools helped us quantify the collected data and fully analyzed all assessment items.

Student #6: The feedback which the instructor gave allowed me to realize the meaning behind the patients’ behavior, that was, their thought.

Student #7: I felt this (i.e. the design) was very good. Although I knew I should conduct the assessment tasks from patients' five aspects of conditions before I had no clear idea about this all the time. This time, however, I could realize how to have a therapeutic talk with patients from the examples which the mobile device provided. I knew what to talk with the patients and the purpose which we talked for.

Student #8: While I conducted the assessment tasks, I would refer to the nursing record to remind myself to include those data. And then I could apply them to do the five aspects of assessment.

Student #8: The examples really helped us write the assignments.

From the statements of participants in focus group interviews, we identified that both the frame and tools provided in this study could improve students' ability to conduct the assessment accurately. The instructor had the same opinions as those of students. She said, those assessment and recording tools allowed students to bring the data with them. That is the most difference between with and without mobile device.

**Mobile device provides more chance of articulation**

In this study, three mechanisms were provided to promote articulation skills, including online discussion forum, on-the-spot discussion and assignments’ sharing. On the whole, students valued all these functions. Their comments were as follows:

Student #3: We students would like to know how to write the final case report and compare them each other. When I logged into the system, I referred to other students’ case report and then I had an idea of how to expand mine.

Student #5: The functions of the various apps surpassed my imagination. Originally, I thought the mobile device just as a tool of recording. I learned much via the usage of mobile device. It saved me a lot of time by viewing other students’ artifacts and discussing with others.

Student #8: The benefit was that we could post our questions to the discussion forum and ask someone to reply them.

As participants indicated, mobile device enabled them to discuss the problem they encounter and provide the opportunity to learn from others’ experience. As for the instructor, she most appreciated using mobile device to have an on-the-spot discussion. She expressed that students could easily use mobile device to show their work to her and immediately solve their problems. Furthermore, the instructor admitted that students
learned a lot by viewing other students’ assignments. She said that students would transfer this imitative learning to their own cases.

**Mobile device promotes the effectiveness of reflection**

With the analysis of transcribed data, reflection was most frequently mentioned as an effective course element. All students appreciated the value that they used mobile device to write daily journal. First, students indicated that it was efficient, as they could immediately write down while they had something still fresh in their memory in the hospital. Furthermore, students reported that the design of reflection journal app helped them make contextual and professional reflection, rather than an unrestrained and vigorous one, that brimmed with talent as previous practicum session. Finally, students admitted that the instant feedback from the instructor gave them in the reflective journal was the most helpful aspect to their self-awareness. Students commented in the interview about how the reflective journal was useful for their clinical learning:

Student #1: For me, mobile device is a handy and convenient tool for my daily work. I could note my thoughts and ideas as they pop up with the reflective journal app. I could also submit the reflective writing assignment with the app conveniently.

Student #2: I think writing these reflective journals is my most gains in this time of practicum. In previous session of practicum, we just wrote the journal routinely; this time we would consider different viewpoints and in turn understood the meaning behind the nursing theory while we wrote it.

Student #6: From the journal, I could realize why I did not attain my goals or what I had learned. I think the instructor’s comment is the main factor.

As described above, participants mentioned that mobile device makes it handy for them to record and reflect on their thoughts, feelings and behaviors during daily activities. Meanwhile, they could also receive instructor’s comments and suggestions. In the interview, the instructor approved the above benefits which students mentioned and indicated that commenting on and correcting students’ reflective journals took her much more time than other tasks during the practicum session. She said:

I had to guide the students to understand themselves well and thus they could follow the beaten path to explore the meaning behind patients’ problems. It was a time-consuming and hard work, but later I could promptly know how much the students had learnt by doing this to gear my teaching to individual student’s needs.

**Mobile device provides the reference data for exploration**

In facilitating exploration, we mainly provided psychiatric nursing resources and concept map for students to help them explore patients’ other aspects of problems. Almost all students reflected that those resources were so useful that they could quickly find the related data. They expressed:

Student #1: I could immediately search the data in mobile device and find the answer whatever the problems I had in the hospital.

Student #3: The difference between with and without using mobile device was that the mobile device presented all of the content of our taking care of patients. These contents were classified so precisely as subjective and objective data that we had good direction in learning. In the previous
practicum, the instructor usually just told us the item which we should write, but not the real content […] As to the concept map, most students said it was useful for their clinical learning. The benefits which they indicated included:

Student #5: It was difficult for me to grasp the key point, but concept map made it easier.

Student #6: Concept map could help us integrate and connect many things, not just rigid concepts.

Student #7: I was impressed and inspired by instructor’s demonstration of using concept map to capture a concise picture of patient’s problems.

Student #8: Concept map guided me to make a summary of my case.

The findings from the focus group interviews indicated that mobile devices have become integral part of their daily work. Mobile devices help them to access information they need. Furthermore, concept map helps them to summarize and organize information into meaningful wholes. The instructor also confirmed the benefits of referring and organizing data which mobile device provided. However, she indicated that it seemed insufficient for students’ explorative learning. The instructor found that although students possessed rich data, some of them still had difficulty in probing the causes of patients’ health problems. She attributed the failure to insufficient nursing knowledge and experience. “Because they could not recognize the meaningful parts of rich data, they would not quickly diagnose patients’ problems”, the instructor said. She suggested that it is necessary to provide more guidance or tools to help students make the decision in the future design.

As the analysis of interview transcripts revealed, using mobile technology in supporting reflection, coaching, scaffolding and articulation was effective, but it was less effective in facilitating modeling and exploration. Similarly, the result in this study is in agreement with a report by Patten et al. (2006) that mobile technology could effectively encourage reflective social practice by focusing on storing information in the learning context for later evaluation and reflection. They further indicated that the reflective applications of mobile devices are most common in medical and teacher educations. As Ranson et al. (2007) discovered the use of personal digital assistant (PDA) in promoting practice reflections in medical education, this study obtained similar result for nursing education. In addition, the effectiveness of using mobile device in scaffolding learning in this study is consistent with the findings of Chen et al. (2008) in their examining mobile devices to scaffold students.

In 2006, Patten et al. investigated applications for handheld devices and questions which of these make full use of the unique attributes of handheld devices to facilitate learning; they argued that the most educationally appropriate applications currently available are built on a combination of collaborative, contextual, constructionist and constructivist principles. The researchers believe that the success of using mobile device in facilitating reflection, coaching, scaffolding and articulating in this study has connection with these principles. Notably, we think our design of mobile learning environment has the contextual focus supporting “field-trip” methodologies of learning. Furthermore, it was found that this environment also followed collaborative principle to enhance participants’ interaction.

However, according to Patten et al. (2006), the reason why exploration was not so effective is that although students were provided with large amounts of nursing resources via app, it did not scaffold or support knowledge construction. They indicated that this kind of app aims to provide referential function of mobile devices and is primarily built upon an
instructional philosophy of learning. They suggested that it will be performed to identify applications informed in constructionist or constructivist principles to help students engage in explorative learning. As the instructor’s suggestions, more guiding tools should be developed to help students make clinical reasoning after they have collected various patient data. Regarding improving modeling, it seems that we can follow the instructor’s proposal, reconsidering the contextual principle and developing some mimic videos to facilitate the instructor’s modeling. Besides, a practical suggestion for improving modeling process made by students was to pay more attention to explaining to them why the communication skill in the video was performed. Stalmeijer et al. (2009) study revealed similar recommendation, in which their medical students expressed that the clinicians could explain more to them why and how they performed certain procedures. These suggestions also reflect a major goal of cognitive apprenticeship: making thinking visible through modeling and articulating the activity in an authentic situation.

**Conclusion**

Cognitive apprenticeship is an important component of nursing education. This study investigated the effects of using mobile device in implementing cognitive apprenticeship model for a clinical nursing practicum. Based on the results of the content analysis of interview data from students and instructor, it revealed that mobile device could adequately support cognitive apprenticeship model, especially in promoting reflection, coaching, scaffolding and articulation. Brown et al. (1989) emphasized the idea of cognitive apprenticeship: “Cognitive apprenticeship supports learning in a domain by enabling students to acquire, develop and use cognitive tools in authentic domain activity”. Within a cognitive partnership framework of instructional technology, computers and other technologies functions as cognitive tools to help students enhance their cognitive powers during thinking, problem-solving and learning (Reeves et al., 1997). When placed in clinical settings, nursing students usually have limited opportunities to access hospital’s computers and other resources such as library. Mobile device thus became a good cognitive tool for students’ clinical learning. Furthermore, it was found that integrating cognitive apprenticeship model with mobile-based learning environment allowed us to develop more realistic applications informed by pedagogical underpinning. Unlike other studies (Garrett and Jackson, 2006; White et al., 2005), therefore, the mobile learning environment in this study allowed students to fully use mobile devices for information referencing, data recording and communication in clinical settings. Yet, further research is needed to develop more tools (e.g. specific Apps for clinical training course) to improve modeling and exploration methods of cognitive apprenticeship model.

**References**


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The informational value of feedback choices for performance and revision in a digital assessment game

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Abstract
Purpose – This study aims to examine the impact of the informational value of feedback choices (confirmatory versus critical feedback) on students’ performance, their choice to revise and the time they spend designing posters and reading feedback in a computer-based assessment game, Posterlet.

Design/methodology/approach – An empirical correlational study was conducted to collect the choices to seek confirmatory or critical feedback and to revise posters in a poster design task from 106 grade 8 students from a middle school in California via Posterlet.

Findings – The results of the study show that critical uninformative feedback is associated with students’ performance, and critical informative feedback is associated with their learning strategies (i.e. feedback dwell time and willingness to revise), while confirmatory informative feedback is negatively associated with both performance and learning strategies.

Research limitations/implications – The study controlled the choice students were given regarding the valence of their feedback but not regarding the informational value of their feedback. Additionally, the study was conducted with middle-school students, and more research is needed to ascertain whether the results generalize to other populations.

Practical implications – The findings can be used to balance the design of the informational content of feedback messages to support student performance in an open-ended, creative design task. This study may also inform the design and implementation of agents (e.g. virtual characters) able to provide user-adaptive feedback for online interactive learning environments.

Originality/value – This study constitutes the first research to examine the informational value of feedback that is chosen rather than received, the latter being the prevalent model of delivering feedback in education.

Keywords Performance, Behavior, Cognition, Feedback, Assessment, Video games

Paper type Research paper

1. Introduction
Teachers spend a considerable amount of time crafting and delivering personalized feedback to their students to provide them with ample information about their task performance (Hattie, 1999; Hattie and Timperley, 2007). Researchers have found large effects of providing feedback on student performance, compared to other educational effects (Butler et al., 2014; Hattie, 2011). Identifying the type of feedback that would work best to improve
students’ performance outcomes is important, and it warrants further research. However, despite a large body of feedback research, the mechanisms of feedback are still not well understood. A recent literature review comparing the effects of feedback characteristics on individuals found that main effects reported in over 64 feedback articles are context-specific and often inconsistent, while the occurrence of feedback characteristics such as the source, message, task and individual characteristics can even invert these main relations (Lechermeyer and Fassnacht, 2018). Moreover, different feedback types (e.g. critical and confirmatory, immediate and delayed, etc.) have yielded mixed results for learning (Kulik and Kulik, 1988), and a meta-analysis found that feedback was even detrimental for performance in a third of the studies analyzed (Kluger and DeNisi, 1998). Feedback effectiveness is further influenced by individual differences, such as fixed versus growth mindset (Dweck and Leggett, 1988). Particularly, researchers differentiated between non-generic and generic feedback based on the informational value of feedback and they indicated that “non-generic feedback refers to a specific event and implies that performance is malleable, while generic feedback implies that task performance reflects an inherent ability” (Chiviacowsky and Drews, 2014).

The information-processing learning theory focuses on individuals’ cognitive ability to use the feedback information they encounter during a learning task not only to reinforce correct answers but also to correct errors (Hattie and Gan, 2011). In the response certitude model, instructional feedback messages include two components: verification and elaboration (Kulhavy and Stock, 1989). Verification feedback indicates whether the answer is right or wrong, while elaboration feedback aids the learner in error correction by including indications on how to correct errors or why an answer is correct (Hattie and Gan, 2011). There is a paucity of studies investigating the impact of non-generic elaboration feedback versus generic feedback on learning. Studies show that students perceive generic feedback as impersonal (Bray, 2016). Moreover, both praise and generic negative feedback were found to be detrimental to performance (Shank, 2017). For instance, in a study where 10-year-old children (n = 40) kicked a soccer-ball at a target, the type of feedback (i.e. generic, such as “You are a great soccer player” versus non-generic, such as “The last kicks were great”) was used to predict motor performance and learning. In their first experiment, researchers found that providing participants with generic feedback resulted in worse performance than providing non-generic feedback, after both groups received negative feedback (Chiviacowsky and Drews, 2014). In their second experiment that focused on the results of a retention task performed one day after practicing a throwing task, researchers showed that participants who received non-generic feedback during the performance significantly outperformed participants in the generic feedback group, after receiving negative feedback.

The current study is novel as it focuses for the first time on the role of the informational value of feedback (i.e. the contribution that the feedback content brings to the task) when students choose between confirmatory (i.e. positive) and critical (i.e. negative) feedback, rather than when students are assigned feedback. In most school settings, the more common approach to feedback delivery is that where teachers assign feedback to students. Specifically, the study examines the relation between the informational value and valence of feedback choices and students’ task performance, choice to revise and time spent reading the feedback and designing posters. Two types of feedback are considered in this study: informative elaboration feedback (i.e. non-generic, task-specific feedback) and uninformative feedback (i.e. generic, non-task specific feedback). Hence, the study poses the following research questions:

**RQ1.** Is informative feedback associated with students’ performance?
RQ2. Is informative feedback associated with students’ willingness to revise their work?

RQ3. Is informative feedback associated with students’ time on task?

The remainder of this article reviews the relevant literature; it describes the Posterlet assessment game that collects students’ feedback and revision choices during a poster design task, and it presents empirical evidence that the informational value of feedback impacts students’ performance, choice to revise and time spent reading feedback and designing posters.

2. Literature review

2.1 Choice-based assessments
Posterlet is a choice-based assessment game (Schwartz and Arena, 2013) that draws on constructivist assessments (Bransford and Schwartz, 1999) and that focuses on the learning processes in which students engage when designing a poster. It collects students’ choices to seek critical (i.e. negative) or confirmatory (i.e. positive) feedback, and it enables the exploration of the impact of students’ choices on performance. Here, the informational value of students’ feedback choices is explored for the first time, with a focus on its impact on performance, choice to revise and the time students spend reading their feedback.

2.2 Performance and feedback value
Deliberate practice research highlights informative feedback as one of the crucial factors in developing mastery (Ericsson et al., 1993). Moreover, many of the cases in which feedback was found to make no difference in learning were using feedback in the form of praise, which can be especially harmful for performance when it is directed to the student, rather than to the task (Brummelman et al., 2014; Burnett and Mandel, 2010; Harris et al., 2015; Hattie and Timperley, 2007). Previous research showed that choosing critical feedback was associated with better learning performance in and outside of an assessment environment (Cutumisu et al., 2015, 2016). This research takes a step further and hypothesizes that students perform better when they encounter critical informative feedback.

2.3 Revision and feedback value
One of the most important factors in deliberate practice is feedback provided by an expert (Ericsson et al., 1993). However, feedback is most effective when learners apply it to revise and improve their performance (Kulik and Kulik, 1988). Although it has been found that feedback information is rarely used in revision of work (Carless, 2006), revision was strongly associated with willingness to choose critical feedback across many studies (Cutumisu et al., 2015; Cutumisu et al., 2016). In this article, the relation between the informational value of feedback and students’ choice to revise is explored for the first time.

2.4 Feedback dwell time, value and time on task
Previous research shows that the more the students choose to seek critical feedback, the more they dwell on feedback (Cutumisu et al., 2015). The current study aims to discern between the impact of informative and uninformative critical feedback on the time students take to read their feedback and design their posters.

2.5 The Posterlet assessment game
The Posterlet game was described in detail in prior research (Cutumisu et al., 2015). The game assessment game tracks two learning choices players make while creating posters: the
choice to seek confirmatory (positive) and critical (negative) feedback about their posters and the choice to revise their posters. In this game, players design three posters to be presented at a booth during their school’s fictitious Fall Fun Fair. On every game round, players design a poster, and then they choose either confirmatory or critical feedback (but not both) from three virtual characters selected from a focus group of animal characters. After reading the feedback, players choose whether to revise their poster. The feedback messages generated by the game were designed to alternate between informative (confirmatory: “Your poster helps people know where to go.” or critical: “Where is the Fall Fair going to be?”) and uninformative (confirmatory: “I like fairs” or critical “I don’t like fairs.”). This study investigates which type of feedback is associated with learning outcomes, depending on the learner’s choices between confirmatory and critical feedback. For instance, if the student makes two same-valence choices on a poster, the first choice is always informative and the second is always uninformative. The game also produces a poster score as the number of tickets sold by each poster booth. An overall poster performance score is computed by adding the poster scores on each game round. Finally, a priority scheme ensured that feedback was assigned based on three broad categories of graphic design principles: crucial information (e.g. the location or date of the poster presentation were not included on the poster canvas), readability (e.g. the font was too small to read) and space use (e.g. the images or text were too close to the edge of the poster or half of the poster was empty).

Posterlet satisfies the three main principles of choice-based assessments by collecting students’ free choices to learn while completing a learning task, their typical learning behaviors induced by the low-stakes game-based assessment environment and by providing opportunities for students to learn during the assessment (e.g. students learn several of the 21 graphic design principles while designing posters and seeking feedback on each of their three posters). The game also provides a creative, open-ended task that facilitates the control of the variables included in this study (e.g. choice of critical or confirmatory feedback, and choice to revise a poster or not), including the measurement of students’ feedback-seeking choices. These free learning choices constitute an indication of students’ readiness to learn on their own. The poster design creative environment is more representative of the types of tasks that students need to solve in real-world learning environments, especially because creativity is quintessential for innovation. This type of task (i.e. poster design) also presents little variation in learners’ prior experience.

3. Methods
3.1 Participants and procedures
The study sampled \( n = 106 \) grade 8 students (60 female, 46 male) from a public middle school in California. Students ranged in age between 13 and 14 years, and they had the same science teacher. They played the Posterlet game in May 2015 designing three posters (\( M = 14.76 \) min, SD = 4.07) individually, as one of the assessments administered during the same testing day. Analyses did not include students who did not provide consent (\( n = 9 \)) or did not complete all posters (\( n = 8 \)). Thus, the analyses included \( n = 89 \) students (50 females and 39 males).

3.2 Measures
3.2.1 Choices. Critical feedback measures students’ willingness to make “I don’t like […]” choices, ranging from 0 (no critical feedback chosen) to 9 (only critical feedback chosen). Feedback is divided into two orthogonal categories: valence (confirmatory or critical) and informational value (informative or uninformative). Revision measures students’ willingness
to revise their posters, ranging from 0 (no poster revised) to 3 (all posters revised). Critical informative feedback measures the number of informative critical feedback messages read by each participant (e.g. “You need to tell them what day the fair is.”), while critical uninformative feedback measures the number of uninformative critical feedback messages read by each participant (e.g. “I don’t really like fairs”). In this study, students chose their feedback valence (confirmatory or critical), not their feedback value (informative or uninformative). Critical feedback represents the sum of the critical informative and critical uninformative feedback. Confirmatory feedback is a complementary measure to critical feedback (i.e. 9 – critical feedback). Thus, confirmatory informative feedback measures the number of informative confirmatory feedback messages (e.g. “It’s good you told them what day the fair is.”), while confirmatory uninformative feedback measures the number of uninformative confirmatory feedback messages encountered (e.g. “I like fairs”). Confirmatory feedback represents the sum of confirmatory informative and confirmatory uninformative feedback. Choices were measured both by round and also across the three rounds of the game. For instance, on a given poster, a player can choose two pieces of critical feedback and one piece of confirmatory feedback. In this case, critical feedback would be two and confirmatory feedback would be one. Furthermore, if the player used one graphic design principle erroneously on a poster, used another one correctly and then chose two pieces of critical feedback and one of confirmatory feedback, then critical informative feedback would be one, critical uninformative feedback would be one and confirmatory informative feedback would be one. At the same time, if a player creates a perfect poster and makes the same choices as above, then the player only receives uninformative critical feedback when seeking critical feedback (i.e. critical informative feedback would be zero, while critical uninformative feedback would be two, while confirmatory informative feedback would still be one).

3.2.2 In-game poster performance. Posterlet generates a poster quality score based on 21 design principles reflecting a student’s poster performance across all rounds of the game. The quality of each poster represents the sum of the scores for each of the 21 features: 1 if a feature is always used correctly on a poster, 0 if a feature is not included on the poster and –1 if a feature is used incorrectly on a poster. Thus, the quality of each poster ranges from –21 to 21. Poster quality represents the sum of the quality of students’ posters measured on each game round: Poster quality 1, Poster quality 2 and Poster quality 3. Therefore, Poster quality ranges from –63 to 63.

3.2.3 Feedback dwell time. Feedback dwell time measures the total amount of time in seconds that students spent reading feedback across the game. The amount of time students spent reading feedback on each game round was also computed as Feedback dwell time 1, Feedback dwell time 2 and Feedback dwell time 3.

3.2.4 Time on task. Design duration measures the time in minutes that students take to design posters. It represents the cumulative time spent designing posters on each game round: Design duration 1, Design duration 2 and Design duration 3. In this study, it took players about 15 min to design all three posters.

4. Results
All analyses were performed using the R open statistical computing environment version 3.4.1 (R Core Team, 2018). The descriptive statistics of the variables included in this study measured across the game are shown in Table I.
4.1 Is informative feedback associated with students’ performance?

Based on the information-processing learning theory, this study hypothesized that informative feedback is associated with students’ performance on the digital posters. Thus, this study explored the association of the informative and uninformative feedback with poster performance by feedback valence (confirmatory or critical). Spearman correlations were conducted between variables, as they were not normally distributed. The results showed that poster quality was positively associated with critical uninformative feedback but not with critical informative feedback, and negatively associated with both informative and uninformative confirmatory feedback, as shown in Table II. Thus, the more the students encounter critical uninformative feedback, the better their posters are. More importantly, the more they encounter confirmatory feedback (informative or uninformative), the worse they perform on their posters.

Next, analyses were conducted by game round. On each of the second and third game rounds, the results revealed that poster performance (Poster quality 2 and Poster quality 3) correlated with critical uninformative feedback and inversely with confirmatory informative feedback, as shown in Table II, consistent with the findings across the game. No correlations were found on the first round, perhaps because students were engaging in exploration and had not yet discovered a clear strategy. These results indicate that better poster performance is associated positively with both types of critical feedback (significantly only with critical uninformative feedback) and negatively with both types of confirmatory feedback (significantly only with confirmatory informative feedback).

Finally, standard linear regression analyses were conducted to determine whether informative and uninformative feedback messages were individual predictors of poster quality (i.e. performance) for each feedback valence. A model composed of critical informative and critical uninformative feedback predicted the poster quality ($F(2,86) = 15.92, p < 0.001, R^2 = 0.27$, adjusted $R^2 = 0.25$), but only critical uninformative feedback ($\beta = 0.54, B = 4.82, p < 0.001, r = 0.52, partial = 0.50, part = 0.50$) was an individual predictor of poster quality.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poster quality</td>
<td>36.58</td>
<td>11.48</td>
<td>-8</td>
<td>56</td>
</tr>
<tr>
<td>Critical informative feedback</td>
<td>3.34</td>
<td>1.18</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Critical uninformative feedback</td>
<td>2.46</td>
<td>1.29</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Confirmatory informative feedback</td>
<td>2.30</td>
<td>1.33</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Confirmatory uninformative feedback</td>
<td>0.90</td>
<td>0.90</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Revision</td>
<td>2.02</td>
<td>1.02</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Feedback duration (seconds)</td>
<td>46.46</td>
<td>12.11</td>
<td>27.02</td>
<td>86.60</td>
</tr>
</tbody>
</table>

**Table I.** Descriptive statistics of the measures included in the study

<table>
<thead>
<tr>
<th>Measure</th>
<th>Critical informative feedback</th>
<th>Critical uninformative feedback</th>
<th>Confirmatory informative feedback</th>
<th>Confirmatory uninformative feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poster quality</td>
<td>0.09</td>
<td>0.52***</td>
<td>-0.36***</td>
<td>-0.32**</td>
</tr>
<tr>
<td>Poster quality round 1</td>
<td>0.20</td>
<td>0.16</td>
<td>-0.20</td>
<td>-0.16</td>
</tr>
<tr>
<td>Poster quality round 2</td>
<td>0.08</td>
<td>0.38***</td>
<td>-0.29**</td>
<td>-0.17</td>
</tr>
<tr>
<td>Poster quality round 3</td>
<td>-0.09</td>
<td>0.50***</td>
<td>-0.27**</td>
<td>-0.34**</td>
</tr>
</tbody>
</table>

**Notes:** The values in italics indicate statistically significant correlations; ***$p < 0.001$; **$p < 0.01$
quality, while critical informative feedback ($\beta = -0.06$, $B = -0.62$, $p = 0.52$, $r = 0.15$, partial = $-0.07$, part = $-0.06$) was not, as shown in Figure 1. This figure illustrates that the more critical uninformative feedback students encounter in Posterlet, the better they perform in the game assessment environment.

A closer look at how performance changes with different levels of critical informative and uninformative feedback is illustrated in Figures 2 and 3. The $x$-axis represents the critical uninformative feedback encountered by the player in Posterlet, the $y$-axis represents the overall performance on the posters across the Posterlet game, while the color coding of the legend located on the right side of the graph represents the critical informative feedback.
encountered by the player. A follow-up analysis was conducted where the interaction between the two types of critical feedback, uninformative and informative, was explored to predict performance. Results revealed that the interaction was significant, showing that critical informative feedback moderates the relation between critical uninformative feedback and performance.

In contrast, a model composed of confirmatory informative and uninformative feedback significantly predicted the poster quality ($F(2,86) = 8.6, p < 0.001$, $R^2 = 0.17$, adjusted $R^2 = 0.15$), but confirmatory informative feedback ($\beta = -0.24, B = -2.1, p = 0.07, r = -0.38$, partial = -0.19, part = -0.18) and confirmatory uninformative feedback ($\beta = -0.20, B = -2.55, p = 0.13, r = -0.37$, partial = -0.16, part = -0.15) were not individual predictors, as shown in Figure 4. Taken together, the results in this section show that, out of all types of feedback examined, critical uninformative feedback is the best predictor of poster quality.

A breakdown of performance by levels of confirmatory informative and uninformative feedback is illustrated in Figure 5. The $x$-axis represents the confirmatory uninformative feedback, the $y$-axis represents the overall performance on the posters across the Posterlet game, while the color coding of the legend on the right side of the graph represents the confirmatory informative feedback encountered by the player in Posterlet.

4.2 Is informative feedback associated with students’ willingness to revise their work?

Previous research showed a strong association between critical feedback chosen and students’ choices to revise their work (Cutumisu et al., 2015; 2016). However, the contribution of each type of feedback, informative and uninformative, to students’ decision to revise their work is not known. The current study explored for the first time the relation between the informational value of feedback and students’ choice to revise. Thus, the study aimed to discern between the impact of the informative and uninformative values of critical and confirmatory feedback on students’ choice to revise their digital posters. Table III shows the average critical feedback, critical informative feedback and critical uninformative feedback encountered by the player. A follow-up analysis was conducted where the interaction between the two types of critical feedback, uninformative and informative, was explored to predict performance. Results revealed that the interaction was significant, showing that critical informative feedback moderates the relation between critical uninformative feedback and performance.
The regression equation shows that the best performance of the players is achieved when they encounter the minimum amount of confirmatory informative feedback (i.e., zero), regardless of the amount of confirmatory uninformative feedback encountered.

Table III. Average and standard deviation of critical feedback by informational value and revision

<table>
<thead>
<tr>
<th>Choice (n = 89)</th>
<th>Critical feedback</th>
<th>Critical informative feedback</th>
<th>Critical uninformative feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>No revision (n = 11)</td>
<td>4.27 (2.76)</td>
<td>2.55 (1.75)</td>
<td>1.73 (1.62)</td>
</tr>
<tr>
<td>Revision (n = 78)</td>
<td>6.01 (1.86)</td>
<td>3.45 (1.04)</td>
<td>2.56 (1.21)</td>
</tr>
</tbody>
</table>
for the students who did not revise any of the three posters and for the students who revised at least one of the three posters.

The results show that students who choose critical feedback more often also decide to revise their posters more often. Students who encounter more critical informative feedback tend to revise more, as do students who encounter more critical uninformative feedback. Table IV shows the equivalent information for confirmatory feedback. Conversely, students who encounter more confirmatory feedback tend to revise less. This trend persisted for students who encountered more confirmatory informative and uninformative feedback. Table V shows the average critical and confirmatory feedback broken down by informational value. The results show that, on average, students chose critical feedback more often than confirmatory feedback across the game.

Spearman correlation analyses investigated which type of feedback (informative or uninformative) was associated with revision for each feedback valence (confirmatory or critical). Across the game, revision was positively associated with critical informative feedback and with critical uninformative feedback, but negatively associated with confirmatory informative feedback and confirmatory uninformative feedback, as shown in Table VI. Moreover, on each game round, revision was positively associated with critical informative feedback and negatively associated with confirmatory informative feedback.

**Table IV.** Average and standard deviation of confirmatory feedback by informational value and revision

<table>
<thead>
<tr>
<th>Choice (n = 89)</th>
<th>Confirmatory feedback</th>
<th>Confirmatory informative feedback</th>
<th>Confirmatory uninformative feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>No revision (n = 11)</td>
<td>4.73 (2.76)</td>
<td>3.18 (1.83)</td>
<td>1.55 (1.13)</td>
</tr>
<tr>
<td>Revision (n = 78)</td>
<td>2.99 (1.86)</td>
<td>2.18 (1.21)</td>
<td>0.81 (0.84)</td>
</tr>
</tbody>
</table>

**Table V.** Average and standard deviation of critical and confirmatory feedback overall and by informational value

<table>
<thead>
<tr>
<th>Choice (n = 89)</th>
<th>All feedback</th>
<th>Informative feedback</th>
<th>Uninformative feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>Critical feedback</td>
<td>5.80 (2.06)</td>
<td>3.34 (1.18)</td>
<td>2.46 (1.29)</td>
</tr>
<tr>
<td>Confirmatory feedback</td>
<td>3.20 (2.06)</td>
<td>2.30 (1.33)</td>
<td>0.90 (0.90)</td>
</tr>
</tbody>
</table>

**Table VI.** Correlations between revision and feedback value overall and by round

<table>
<thead>
<tr>
<th>Choice (n = 89)</th>
<th>Critical informative feedback</th>
<th>Critical uninformative feedback</th>
<th>Confirmatory informative feedback</th>
<th>Confirmatory uninformative feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revision</td>
<td>0.32**</td>
<td>0.39***</td>
<td>-0.32***</td>
<td>-0.42***</td>
</tr>
<tr>
<td>Revision 1</td>
<td>0.24*</td>
<td>0.29**</td>
<td>-0.24*</td>
<td>-0.29*</td>
</tr>
<tr>
<td>Revision 2</td>
<td>0.24*</td>
<td>-0.03</td>
<td>-0.18</td>
<td>-0.04</td>
</tr>
<tr>
<td>Revision 3</td>
<td>0.32**</td>
<td>0.41***</td>
<td>-0.34**</td>
<td>-0.51***</td>
</tr>
</tbody>
</table>

Notes: The values in italics indicate statistically significant correlations; ***p < 0.001; **p < 0.01; *p < 0.05
Standard linear regression analyses were conducted to determine whether informative and uninformative feedback messages were individual predictors of revision, for each of the two feedback valences, critical and confirmatory, respectively. A model composed of critical informative and critical uninformative feedback significantly predicted revision ($F(2, 86) = 8.84, p < 0.001, R^2 = 0.17, \text{adjusted } R^2 = 0.15$) and both critical informative ($\beta = 0.24, B = 0.21, p = 0.02, r = 0.34, \text{partial} = 0.24, \text{part} = 0.23$) and uninformative ($\beta = 0.25, B = 0.20, p = 0.02, r = 0.35, \text{partial} = 0.24, \text{part} = 0.23$) feedback were individual and medium predictors of revision, as shown in Figure 6.

In contrast, a model composed of confirmatory informative and confirmatory uninformative feedback significantly predicted revision ($F(2, 86) = 10.01, p < 0.001, R^2 = 0.19, \text{adjusted } R^2 = 0.17$), but only confirmatory uninformative feedback ($\beta = -0.35, B = -0.40, p < 0.01, r = -0.43, \text{partial} = -0.28, \text{part} = -0.26$) significantly and negatively predicted revision, while confirmatory informative feedback was not a significant predictor ($\beta = -0.11, B = -0.08, p = 0.42, r = -0.35, \text{partial} = -0.09, \text{part} = -0.08$) (Figure 7).

Additionally, the study aimed to explore the role of the different type and valences of feedback in moderating the relation between revision and performance. Thus, a standard linear regression analysis was conducted where critical and confirmatory informative and uninformative feedback were regressed on performance. Analyses showed that, of all the feedback types and valences, critical uninformative feedback was the sole predictor of performance, but there was no interaction between revision and any type of feedback and valence in predicting performance. Thus, critical uninformative feedback does not moderate the relation between revision and performance, as shown in Figures 8 and 9.

4.3 Is informative feedback associated with students’ time on task?

Research found that choosing critical feedback was associated with longer feedback dwell time (i.e. students examined feedback for a longer time the more they chose critical feedback over confirmatory feedback). However, it is not known whether this prolonged dwell time is associated with reading more informative or more uninformative critical feedback. Thus, the
current study set out to explore the association between critical informative feedback chosen by students and students’ total feedback dwell time across the game. Spearman correlation analyses were conducted to investigate whether informative and uninformative feedback messages were differentially associated with the time students spent reading feedback, as well as with the time students spent designing their posters (i.e. time on task). The last round of the game was closely examined, when students presumably had found a stable learning strategy, judging by the significant differences from the first to the second round of the

Figure 7.
Only confirmatory uninformative feedback is a significant and negative predictor of revision.

Figure 8.
Although critical uninformative feedback predicts performance, it does not moderate the relation between students’ choices to revise and their poster performance.
On round three, the amount of time students took to read feedback was associated positively with critical informative feedback and negatively with confirmatory uninformative feedback, as shown in Table VII. This indicates that the more the students encounter critical informative feedback, the more time they spend reading feedback on the last round of the game. Conversely, the more time the students encounter confirmatory uninformative feedback, the less time they spend reading feedback on the last game round.

The association between students’ time on task (i.e. the amount of time students took to design each poster) and the informational value of critical and confirmatory feedback was also examined. The results shown in Table VIII revealed that, although significant only for the second round of the game, students’ time on task was positively associated with critical feedback (both informative and uninformative) and negatively with confirmatory feedback (both informative and uninformative).

<table>
<thead>
<tr>
<th>Choice (n = 89)</th>
<th>Critical informative feedback</th>
<th>Critical uninformative feedback</th>
<th>Confirmatory informative feedback</th>
<th>Confirmatory uninformative feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feedback dwell time</td>
<td>-0.16</td>
<td>-0.18</td>
<td>0.14</td>
<td>0.24*</td>
</tr>
<tr>
<td>Feedback dwell time 1</td>
<td>-0.11</td>
<td>-0.24*</td>
<td>0.11</td>
<td>0.24*</td>
</tr>
<tr>
<td>Feedback dwell time 2</td>
<td>-0.14</td>
<td>-0.11</td>
<td>0.14</td>
<td>0.13</td>
</tr>
<tr>
<td>Feedback dwell time 3</td>
<td>0.22*</td>
<td>0.11</td>
<td>-0.13</td>
<td>-0.22*</td>
</tr>
</tbody>
</table>

**Notes:** The values in italics indicate statistically significant correlations; *p < 0.05
5. Discussion

5.1 Performance and feedback value

The game did not provide a tutorial; thus, the first round of the game was an opportunity for students to explore the digital environment. The results revealed that students who encountered critical uninformative feedback more often also performed better on their posters. Although the association between poster performance and critical informative feedback was positive, it did not reach significance. When the individual contributions of the informative and uninformative feedback for each feedback valence in predicting poster performance were examined, critical uninformative feedback emerged as the only significant predictor. It is surprising that uninformative critical feedback proved to be more helpful for performance than informative critical feedback. One possible explanation is that students strive to identify the shortcomings of their posters when they encounter critical uninformative feedback; thus, they work harder on subsequent posters. The results also showed that the fewer confirmatory informative feedback messages students encountered, the better they performed on the poster design tasks. This result supports previous findings that confirmatory feedback, and especially praise or confirmatory uninformative feedback, may be harmful for performance (Hattie and Timperley, 2007), as it contains little task information (Shank, 2017; Shute, 2008). This result also suggests that students may already know the information provided by the confirmatory informative feedback; thus, they may only improve their poster designs when they read critical informative feedback that fills a gap in their poster design knowledge. This hypothesis is supported by the findings related to revision and the informative value of feedback showing that the more the students encounter critical (informative and uninformative) feedback, and the less they encounter confirmatory (informative and uninformative) feedback, the more they revise their posters. However, it could be that students who usually revise their work are more drawn to seeking critical rather than confirmatory feedback. Taken together, these results warrant further investigation. When examining the associations of the different feedback types, feedback dwell time and time on task over each of the last two rounds of the game, results revealed that students spent more time reading the feedback and designing posters when they encountered more critical informative rather than uninformative feedback. This finding suggests that critical informative feedback may be more important than both critical uninformative feedback and confirmatory feedback, which was our initial hypothesis. A follow-up study that is planned to collect more data will include a learning post-test to further clarify the relation between critical informative feedback and performance. This was not possible for the current study due to the limited time allotted for this assessment among a battery of assessments administered to the students during one class period. The new study will also control directly the informational value of the feedback of each valence to elucidate the specific role of this feedback characteristic.

Table VIII.
Correlations between poster design duration and feedback value overall and by round

<table>
<thead>
<tr>
<th>Choice (n = 89)</th>
<th>Critical informative feedback</th>
<th>Critical uninformative feedback</th>
<th>Confirmatory informative feedback</th>
<th>Confirmatory uninformative feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>Design duration</td>
<td>0.02</td>
<td>0.05</td>
<td>-0.10</td>
<td>0.005</td>
</tr>
<tr>
<td>Design duration 1</td>
<td>0.15</td>
<td>-0.002</td>
<td>-0.15</td>
<td>0.002</td>
</tr>
<tr>
<td>Design duration 2</td>
<td>0.23*</td>
<td>0.21*</td>
<td>-0.27*</td>
<td>-0.22*</td>
</tr>
<tr>
<td>Design duration 3</td>
<td>0.08</td>
<td>0.12</td>
<td>-0.11</td>
<td>-0.12</td>
</tr>
</tbody>
</table>

Notes: The values in italics indicate statistically significant correlations; *p < 0.05
5.2 Revision and feedback value
The findings showed that the more the students encountered critical feedback (both informative and uninformative) and the less they encountered confirmatory feedback (both informative and uninformative), the more they chose to revise. Overall, students chose more than the average amount of critical feedback and less than the average amount of confirmatory feedback across the game. Due to the design of the informational value of feedback, students encountered a higher amount of informative than uninformative feedback for each feedback valence. The results broken down by students who revised their posters at least once and students who never revised their posters showed that students who more frequently chose critical than confirmatory feedback also revised more, supporting prior research (Cutumisu et al., 2015, 2016). Conversely, students who more frequently chose confirmatory feedback also revised their posters less often. This result indicates that, for revision, the valence of feedback may be more important than the informational value of feedback, especially as critical and confirmatory informative feedback messages were designed to be equivalent in informational value and length in Posterlet. Moreover, this result was consistent on each game round as well. Thus, within the same feedback valence, the informative and uninformative feedback messages seem to be equally important. When examining the individual contributions of the informative and uninformative feedback for each feedback valence in predicting revision, informative and uninformative feedback messages were equivalent, significant and unique predictors of revision for both critical and confirmatory feedback. These results show that the choice to revise is impacted by the valence of the feedback choice more than by its informational value. Critical feedback seems to determine students to try harder and revise their work (e.g. fix mistakes pointed out by the feedback), regardless of its specificity.

5.3 Feedback dwell time, time on task and feedback value
On the last game round, the findings indicate that the more the students encountered critical informative feedback and the less they encountered confirmatory uninformative feedback, the more time they spent reading feedback. Overall, this result is consistent with previous research showing that the more the students choose to seek critical feedback, the more they dwell on feedback (Cutumisu et al., 2015). This result suggests that, yet again, it is critical informative feedback that is associated with better outcomes. The finding also suggests that the more the students encounter confirmatory uninformative feedback, the less attention they pay to this type of feedback, as dwell time provides insight into individuals' attention and processing of feedback. The results also showed that students’ time on task was positively associated with critical feedback (both informative and uninformative) and negatively with confirmatory feedback (both informative and uninformative), although significantly only on the second round of the game. The time on task also includes the amount of time it takes students to revise their posters, indicating a possible path to mastery through revision based on feedback. As this is not a causal study, it could be that students who are higher achievers in general also apply good learning strategies to any of their tasks (e.g. critical feedback seeing or choosing to revise their posters). Taken together, these results support the findings regarding performance and revision and highlight the importance of critical over confirmatory feedback in the levels of attention that individuals allot to their work.

5.4 Limitations and future work
In Posterlet, students are given a choice regarding the valence of their feedback, but not regarding the informational value of feedback. The feedback system embedded in the
Posterlet game is designed to alternate between informative and uninformative feedback of the same valence. For example, when choosing three pieces of critical feedback on a poster, the student may encounter two critical informative feedback messages and one critical uninformative feedback message. Moreover, if the student makes no design mistakes and chooses critical feedback, uninformative critical feedback is presented instead of critical informative feedback. Thus, a future experimental study will control both the valence and the informative value of the feedback students choose. In that case, would students choose more informative or more uninformative feedback, and would they prefer critical over confirmatory feedback? Consequently, what would the students’ performance be in each of these cases? Also, a follow-up study will explore the relation between feedback value and other factors, such as academic achievement and mindset. Finally, the strengths of the associations between learning choices and performance have been replicated in studies with many different types of learners, but future studies will explore whether these results regarding the informational value of feedback can generalize to other demographics beyond middle-school students.

5.5 Educational implications
This research will advance our understanding of feedback processes, with a theoretical impact on understanding the underpinnings of the informational value of critical, constructive feedback-seeking through an empirical evidence base, including how feedback is processed in terms of time allotted by individuals on the task and on the various types of feedback and how different types of feedback influence performance outcomes. The findings may provide instructors with better tools for exchanging feedback with their students effectively. The results of this study extend the cumulative body of research on how feedback affects performance and learning. Finally, the findings of this study may be used in the design and implementation of agents (e.g. virtual characters) that can provide more balanced informational types of user-adaptive feedback for online interactive learning environments.

6. Conclusions
This research examined the impact of the informational value of feedback on students’ performance, willingness to revise, and time spent reading feedback and designing posters. The findings showed that students’ performance was positively associated with the critical uninformative feedback that they encountered and negatively associated with the confirmatory informative feedback that they encountered in the Posterlet digital assessment game. Moreover, students’ choice to revise was positively associated with the critical informative and uninformative feedback that they encountered, and negatively associated with the confirmatory uninformative that they encountered in the game. On the last round of the game, the findings indicate that the more time the students spent reading feedback, the more critical informative feedback and the less confirmatory uninformative feedback they encountered on that round. The data provide evidence that critical uninformative feedback is helpful for performance, critical informative feedback is helpful for revision and time on task, but confirmatory informative feedback is detrimental for performance, for students’ willingness to revise their work, and for the time they spend reading feedback in a digital poster design task. These findings constitute a first step in gaining an insight into the value of feedback and its impact on performance and learning choices. This research has implications for the design of assessments and instructional materials that may help students become more proactive regarding their feedback and more intentional about
revising their work. Consequently, these findings may help students apply good learning behaviors to improve their performance.

References


Hattie, J. (1999), Influences on Student Learning, (Inaugural Lecture: Professor of Education ed.), University of Auckland.


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