Learning Analytics in Higher Education using Peer-feedback and Self-assessment: Use Case of an Academic Writing Course

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Abstract: The growing prevalence of learner-centred forms of learning as well as an increase in the number of learners actively participating on a wide range of digital platforms and devices give rise to an ever-increasing stream of learning data. Learning analytics (LA) may enable learners, teachers, and their institutions to better understand and predict learning and performance. However, the pedagogical perspective and matters of learning design have been underrepresented in research thus far. We identify technology-supported peer-feedback and self-assessment as particularly promising from an educational point of view. We present a use case to demonstrate how these measures can be implemented. Using the technology acceptance model and a sample of 484 undergraduate students, we identify factors for a successful implementation of technology-supported peer-feedback and self-assessment.

1 INTRODUCTION

Big data and analytics are burgeoning fields of research and development (Abdous and Yen, 2012; Ali et al., 2012; Dyckhoff et al., 2012). In education, several concurrent developments are taking place that have implications for big data and analytics in the field of learning. A wide range of promises and anxieties about the coming era of big data and learning analytics (LA) are in debate (Cope and Kalantzis, 2016; Ifenthaler, 2015; Ifenthaler, 2014). Overall, there is widespread consensus that the educational landscape itself is in transition and the changes are substantial, with expository instructional methods being replaced by more learner-centred approaches to learning. As more and more learning is either taking place online or is supported through technology, these active learners produce an ever increasing stream of data – both inside learning management systems (LMS) and outside, in other IT-based environments (Pardo and Kloos, 2011).

LA refers to the use of "dynamic information about learners and learning environments to assess, elicit, and analyze them for modeling, prediction, and optimization of learning processes" (Mah, 2016, p. 288). As Roberts et al. (2017, p. 317) states: the pedagogical potential is to provide students "with some level of control over learning analytics as a means to increasing self-regulated learning and academic achievement". Visualisation of information, social network analysis and educational data mining techniques are at the methodological core of this newly emerging field (Greller and Drachsler, 2012). Techniques for analyzing big data are such as machine learning and natural language processing based on the particular characteristics of these data for learner and teacher feedback, the possibility of real-time governance, and educational research (Cope and Kalantzis, 2016, p. 2).

While this field is multidisciplinary, the pedagogical perspective appears to be somewhat underrepresented (Greller and Drachsler, 2012). Current research on big data in education revolves largely around the potential of learning analytics to increase the efficiency and effectiveness of educational processes. Accordingly, the main problem is that the core focus of research is on prediction, while the potential for supporting reflection on processes of learning has largely been neglected (Seufert and Meier, 2019). However, there is evidence for a high impact of peer-feedback and self-assessment, as a manifestation of reflection, on learning outcomes (Hattie and Timperley, 2007; Nicol and Macfarlane-Dick, 2006). In this regard, students may act as their own learning analytics using their own data. We illustrate this idea by presenting a use case. However, students might not utilize these

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valuable resources outside the formal setting of the use case. To get a better inside in the determinants of students' (voluntarily) use, we rely on the technology acceptance model (TAM).

In this light, the aim of the paper is to investigate determinants for students' acceptance of online peer-feedback and self-assessment.

2 PEER-FEEDBACK AND SELF-ASSESSMENT

2.1 The Impact of Peer-feedback and Self-assessment

In line with Kelly, Thompson and Yeoman (2015), the claim that we put forth in this paper is that "theory-led design has the potential to yield innovation in the development of LA tools and, in turn, that the development of LA tools and their use may contribute to learning theory" (p. 15).

Feedback has among the highest influence on learning outcomes (Hattie and Timperly, 2007). As Evans (2013) discovered in a thematic analysis of the research evidence on assessment feedback in higher education (based on over 460 articles over a time span of 12 years), effective online formative assessment can enhance learner engagement during a semester class.

Focused interventions (e.g., self-checking feedback sheets, mini writing assessments) can make a difference to student learning outcomes as long as their value for the learning process is made explicit to and is accepted by students. The development of self-assessment skills requires appropriate scaffolding on the part of the lecturer working with the students to achieve co-regulation (Evans, 2013). Hence, we define digital learning assessments as "the use of ICT to support the iterative process of gathering and analyzing information about student learning by teachers as well as learners and of evaluating it in relation to prior achievement and attainment of intended, as well as unintended learning outcomes" (Pachler et al. 2010, p. 716).

High quality feedback may facilitate the development of self-assessment skills (Nicol and Macfarlane-Dick, 2006), which is regarded as a precondition for lifelong learning.

2.2 Use Case: Peer-feedback and Self-assessment and in an Academic Writing Course

2.2.1 Context

We have implemented technology-supported peer-feedback and self-assessment in a University beginner's course (see figure 1). The utilized tools can be deemed as dashboard applications (Verbert et al., 2013). In total, 1615 students attended the course. They are split up in groups of less than 24 persons. In every group, a lecturer supports students during their

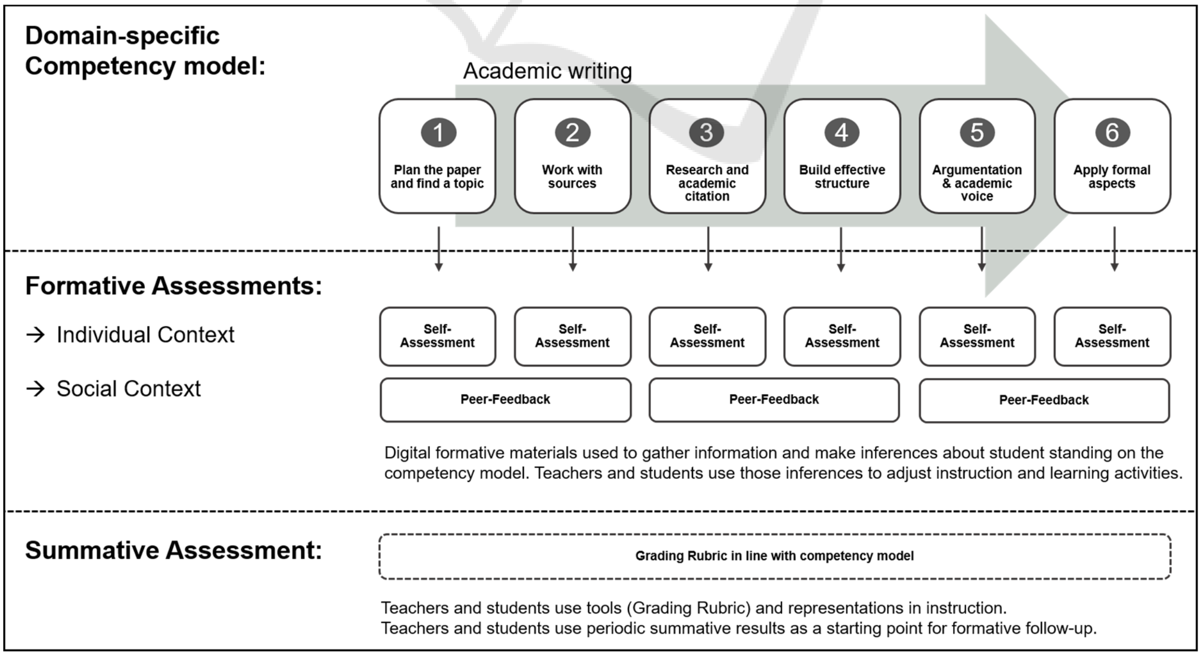

Figure 1: Use case: Academic writing (own illustration).

learning. We utilize “Fronter v10 by itslearning” and “Loom v2.9.15” as learning management systems (LMS) to cope with the complexity of this large-scale course. In the future, we will rely on “Canvas by Instructure” as LMS.

A competency model of academic writing structures the learning process and peer-feedback as well as self-assessment. The model consists of six development steps in academic writing. These units correspond to the six units of the course (see figure 1). For a detailed description, see Seufert and Spiroudis (2017). Our intention is to encourage students to use domain-specific and theoretically founded criteria to analyse their own work and that of others. We think it is important to make students aware that analysis and inferences should be informed by theory rather than driven by the available data.

2.2.2 Peer-feedback

Right in the beginning of the course, lecturers inform students about the decisive role of feedback in the learning process from an educational point of view. After every two units, students are supposed to provide peer-feedback to the writing products of their fellow students. To ensure high-quality feedback, students receive an in-depth instruction on the feedback process and the domain-specific competency model. To this end, we use learning videos and direct instruction during the lectures. Drawing on this knowledge, students assess the writing products, e.g. research question and abstract, of two randomly assigned fellow students. We scaffold the process by providing templates for evaluation. Students are required to address positive and negative aspects as well as concrete measures of improvement. After the peer-feedback phase, the lecturer reviews selected writing products and peer-feedbacks. The LMS supports her/him in the selection process. Good and bad practices of academic writing are discussed within the groups. Furthermore, the lecturer addresses the quality of the feedback. This aims at fostering students’ ability to provide valuable feedback. The described measures can be deemed as formative assessments in individual and social contexts. We regard technology-supported peer-feedback as promising in many ways. In large-scale courses, it is not feasible to give detailed feedback on a regular basis to every single student. However, by means of peer-feedback, we are able to cover learning goals on a high taxonomy level of our competency model. This would be not feasible using selected response tasks. Moreover, we train a decisive competence – providing and receiving feedback. Through this process of in-depth dealing with the subject matter, students might substantially increase their academic writing skills. The LMS allows the lecturer to allocate his/her time in an efficient way, which is especially important in large-scale courses. This may include focussing on students with special needs. Moreover, typical mistakes can easily be identified and thematised in instruction.

2.2.3 Self-assessment

During the first group session, the lecturer introduces the students to the idea behind self-assessment and its pedagogical objectives. The self-assessment is on a voluntarily basis and can be done and repeated at any time. However, the LMS reminds the student before the unit and suggests taking part in the self-assessment. The self-assessment comprises three elements: A self-evaluation, a computer-based-assessment, and an optional peer-comparison of the results. Concerning self-evaluation, students rate their current competence level, e.g. of ‘work with sources’ on a percentage scale using the competency model. Afterwards they answer test items that consist of selected response questions and therefore can automatically be scored. This makes the instrument suitable for large-scale courses. The results are presented in the dashboard where students can compare their test results with their self-evaluation as well as with the results of their peers. In a last step, students are requested to analyse their knowledge gaps, to define next steps, and to reflect the self-assessment process. To ensure an anxiety-free learning and reflection environment, lecturers do not have access to the individual results. However, they can watch the aggregated learning results of their group. If they noticed deficits or abnormalities, they may address these issues in the next unit.

3 STUDENTS’ ACCEPTANCE OF PEER-FEEDBACK AND SELF-ASSESSMENT

3.1 Method

3.1.1 Sample

Prior to the beginning of the mandatory academic writing course for first semester bachelors students, we asked all 1615 participants to fill in an online-questionnaire. We obtained 484 responses. The average student in the sample is aged 19.51 years (SD

= 1.44). 266 (54.94%) students in our sample come from the German speaking part of Switzerland, 67 (13.84%) from the French speaking part, 36 (7.44%) from the Italian speaking part; 66 (13.64%) are from Germany and 49 (10.14%) from other countries. Overall, 62.19% in the sample are females.

3.1.2 Theoretical Framework and Analysis

In line with Park (2009), we used a refined version of the TAM to determine the intention to use peer-feedback and self-assessment. Drivers for the behavioural intention (BI) are attitude towards the behaviour (AT), perceived usefulness (PU), perceived ease of use (PE), social norms (SN), and self-efficacy (SE). Drawing on his work, we have developed items for measuring the constructs: BI (2 items, e.g. “I intend to be a heavy user of online-self-assessment”), AT (2 items, e.g. “I am positive toward online-self-assessment.”), PU (3 items, e.g. “Online-self-assessment would improve my learning performance.”), PE (3 items, “I find online-self-assessment easy to use.”), SN (2 items, “My peer-group would like me to use online-self-assessment.”), and SE (2 items, “I feel confident using online-self-assessment.”). The items are measured on a 7-point rating scale, ranging from 1 “entirely disagree” to 7 “entirely agree”.

We use partial least squares structural equation modelling (PLS-SEM, SMART-PLS 3.2.7). PLS-SEM may be (in comparison to CB-SEM) the suitable approach because we aim at predicting BI (Hair, Ringle, and Sarstedt, 2011). Moreover, SN is measured using a formative measurement model, and our items are not normally distributed (Shapiro-Wilk test: $p < .05$) which also suggests using PLS-SEM (Hair, Ringle, and Sarstedt, 2011).

PLS-SEMs are interpreted in two steps: evaluation of the measurement model and assessment of the structural model that deals with the relationships between the constructs. PLS-SEM also offers a method that allows us to identify the most important drivers for BI: importance-performance-map analysis (IPMA) (Ringle and Sarstedt, 2016). In our case, IPMA shows how the five constructs are shaping BI, which considers direct and indirect effects (importance [I]). Effects are calculated using unstandardized path coefficients. Students’ average latent variable scores on a percentage scale indicate the performance (P). The goal is to identify those constructs that have a relatively high importance for BI (i.e. those that have a strong total effect), but also have a relatively low performance (i.e. low average latent variable scores). We considered all direct and indirect paths as claimed by Park (2009).

3.2 Results

3.2.1 Peer-Feedback

The measurement model is sound in every respect (Hair, Sarstedt, Ringle, and Mena, 2012; Hensler, Ringle, and Sarstedt, 2015), see table 1. The measures are reliable, indicated by Cronbach’s alpha and composite reliability above .70. Convergent validity is established as all standardized factor loadings exceed .70. Hence, for every construct, the average variance extracted (AVE) is greater than .50, which indicates convergent validity. Discriminant validity might be ensured because the square roots of AVE are always higher than the correlations among the constructs (Fornell-Larcker criterion). Moreover, the SRMR is .057 and below the threshold of .06 (Hu and Bentler, 1999).

Table 1: Quality of measurement model: peer-feedback.

				Square root of *AVE* on diagonal/ Correlations among constructs					
Construct	α	ρc	AVE	(1)	(2)	(3)	(4)	(5)	(6)
(1) Attitudes (AT)	0.85	0.93	0.87	.93					
(2) Ease of use (PE)	0.90	0.94	0.83	.40	.91				
(3) Self efficacy (SE)	0.72	0.88	0.78	.54	.63	.88			
(4) Social norms (SN)		n/a		.53	.37	.51	n/a		
(5) Intention to Use (BI)	0.85	0.93	0.87	.56	.24	.45	.50	.93	
(6) Usefulness (PU)	0.89	0.93	0.82	.80	.44	.52	.54	.51	.90

Note. α = Cronbach’s alpha; ρ_c = composite reliability; *AVE* = average variance extracted. Social norms: Formative measurement model.

Figure 3 depicts the path model for predicting the use of peer-feedback. Like Park (2009), we considered direct and indirect relationships. We found the following significant total effects on BI: AT (β = 0.283, p <.001), PU (β = 0.303, p <.001), SN (β = 0.367, p <.001), and SE (β = 0.265, p <.001. However, PE does not significantly affect BI (β = -.096, p = .069).

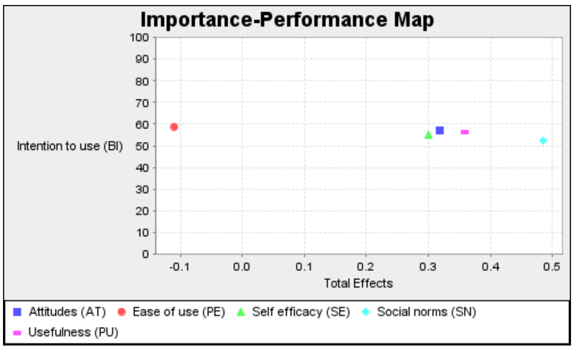

Figure 2: Importance performance map analysis for peer-feedback (n=484).

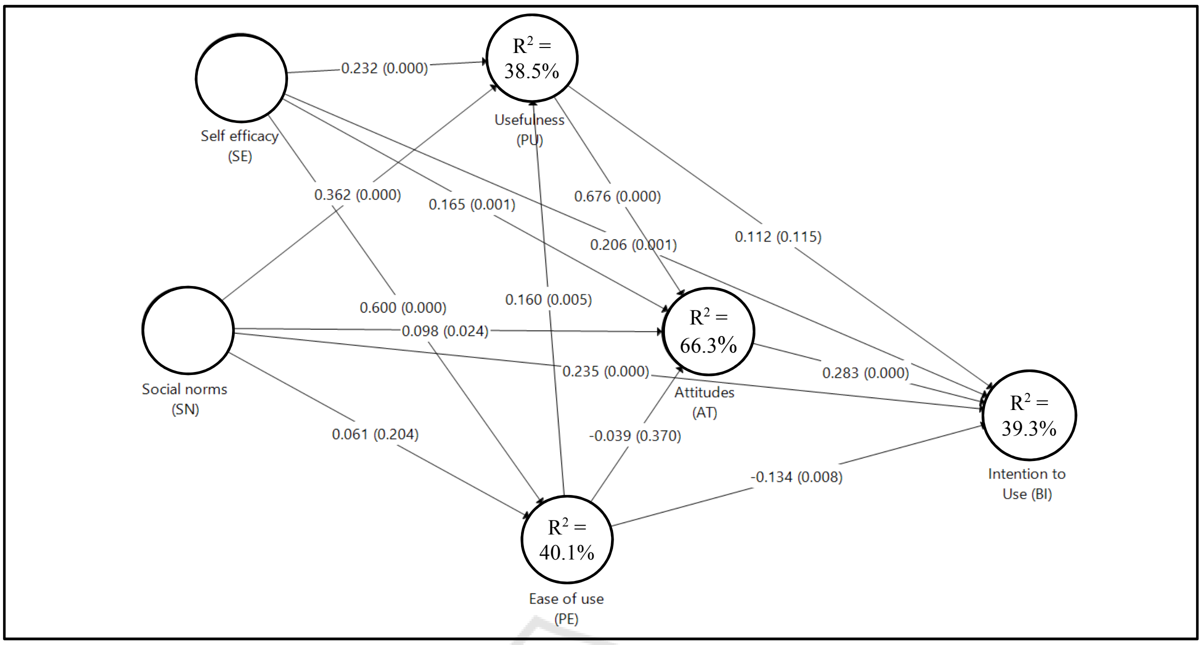

Figure 3: Path model peer-feedback (n=484).

IPMA, see figure 2, indicates that all determinants of BI show substantial room for improvement; the performance never exceeds 60%. Concerning importance, SN shows the highest impact on BI. The performance of SN is slightly lower than that of the other determinants. PU, PA, and SE yield similar performance.

3.2.2 Self-assessment

The quality of the measurement model for self-assessment is high. The measures show decent reliability, indicated by Cronbach's alpha and composite reliability above .80. Convergent validity is established as all standardized factor loadings exceed .70 and AVE is always greater than .50, which is evidence for convergent validity. Discriminant validity may also be ensured because the square roots of AVE are always higher than the correlations among the constructs (Fornell-Larcker criterion). The SRMR equals .050, which is sufficiently low. The assessment of the measurement model is summarized in table 2.

Table 2: Quality of measurement model: self-assessment.

				Square root of *AVE* on diagonal/ Correlations among constructs					
Construct	α	ρc	AVE	(1)	(2)	(3)	(4)	(5)	(6)
(1) Attitudes (AT)	0.90	0.95	0.91	.95					
(2) Ease of use (PE)	0.92	0.95	0.86	.55	.93				
(3) Self efficacy (SE)	0.82	0.85	0.85	.64	.74	.92			
(4) Social norms (SN)		n/a		.47	.39	.45	n/a		
(5) Intention to Use (BI)	0.83	0.92	0.85	.62	.39	.50	.46	.92	
(6) Usefulness (PU)	0.89	0.95	0.86	.83	.58	.60	.49	.56	.93

Note. α = Cronbach's alpha; ρ_c = composite reliability; *AVE* = average variance extracted. Social norms: Formative measurement model.

We find the following significant total effects on BI: AT (β = 0.391, p <.001), PU (β = 0.353, p <.001), SN (β = 0.291, p <.001), and SE (β = 0.372, p <.001). However, PE (β = -0.007, p = .991) does not significantly affect BI. Figure 5 depicts the SEM for self-assessment. Figure 4 shows the IPMA results. AT has the strongest influence on BI (importance), followed by PU, SE, and SN. In terms of performance, all constructs offer potential for increase as they are below 64%.

3.3 Discussion

The measurement models are sound in terms of reliability and convergent as well as discriminant validity. Moreover, SRMR is below .06, which is sufficiently low (Hu and Bentler, 1999).

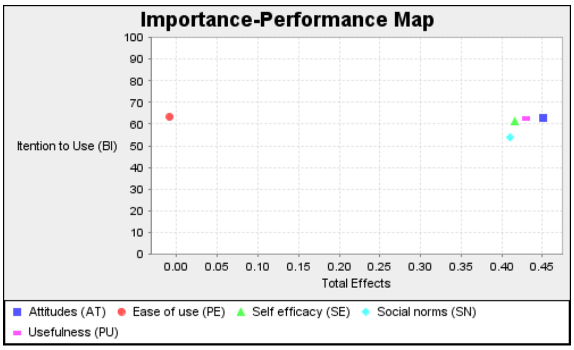

Figure 4: Importance performance map analysis for self-assessment (n=484).

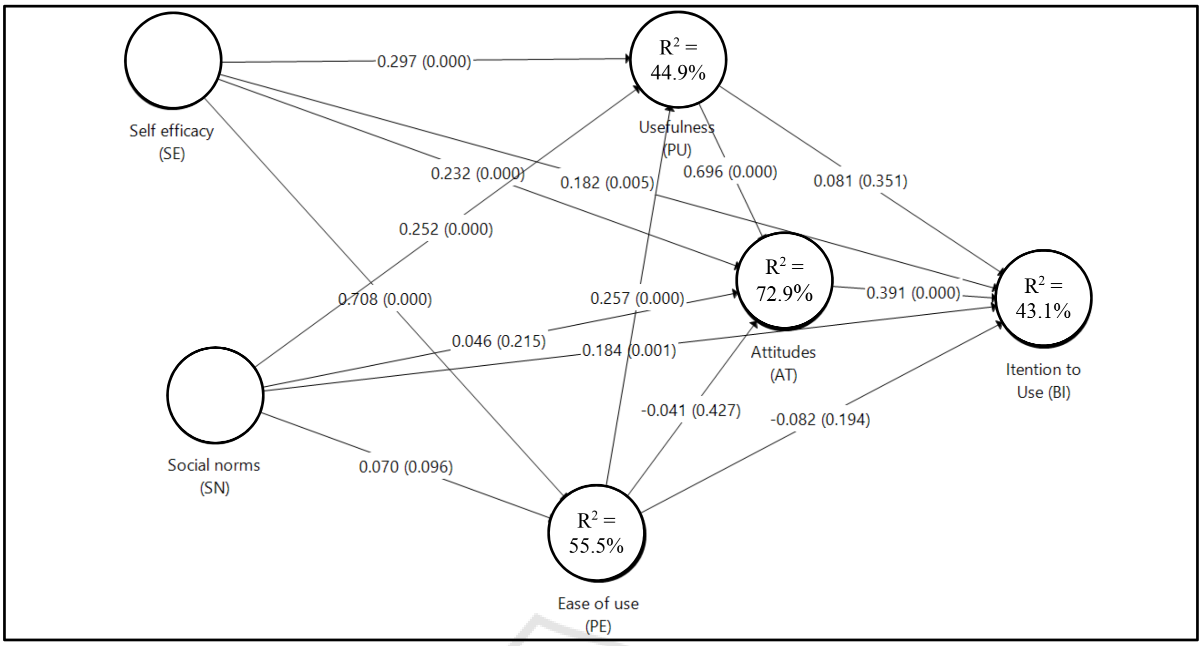

Figure 5: Path model self-assessment (n=484).

Therefore, the items might be suitable for operationalizing the constructs for evaluating students' acceptance of peer-feedback and self-assessment. The predictive power is sufficiently high. For the intention to use peer-feedback, R^2 equals 39.3%, for self-assessment 43.1%. Thus, we regard the model as useful for explaining students' intention to use peer-feedback and self-assessment.

Intention to use peer-feedback and self-assessment both show potential for increase. Currently, the performance is 41.4% and 49.4%, respectively. In other words, students rather not have the intention to use those means. This is an issue because peer-feedback and self-assessment are decisive building blocks in a lifelong learning process.

In terms of peer-feedback, social norms have the highest influence on intention to use and a moderate performance (I = 0.486, P = 52.4%). Since we use a formative measurement model, we are able to split up this effect. The effect can mainly be attributed to the influence of the peer group. Perceived usefulness has also an important influence on the intention to use peer-feedback (I = 0.358, P = 56.4%). Self-efficacy concerning the ability to provide valuable feedback plays also a considerable role for the intention to use peer-feedback (I = 0.300, P = 55.2%). Like Park (2009), we did not find a significant influence of perceived ease of use on behavioural intentions. Students might accept reasonable effort to make themselves familiar with the necessary instruments. Nevertheless, we regard user-friendly platforms as vital because ease of use significantly and positively influences perceived usefulness.

Concerning self-assessment, positive attitudes have the highest impact on behavioural intentions (I = 0.451, P = 62.8%). Positive attitudes themselves are heavily influenced by perceived usefulness (I = 0.736, 62.6%) and self-efficacy (I = .520, P = 62.3%). Both have also a considerable impact on behavioural intentions: I = 0.430 and 0.416, respectively.
Again, perceived ease of use does not influence behavioural intentions.

Comparing the results for peer-feedback and self-assessment, the main difference is that social norms play in comparison to the other drivers a smaller role for self-assessment. This is not surprising as peer-feedback includes by nature a social component.

The survey was voluntary and yielded a response rate of 30%. However, self-selection effect may be a threat to the validity of the results.

3.4 Practical Implication

Social norms in form of perceptions of the peer group are especially important for the intention to use peer-feedback. Lecturers may therefore aim at establishing a positive and commonly shared sentiment towards this instrument.

In terms of peer-feedback and self-assessment, lecturers might create positive attitudes by demonstrating their usefulness. Since an important part of usefulness is the perceived learning outcome, lecturers might present research results about the high impact of feedback and self-assessment on learning outcomes. Moreover, by using peer-feedback and self-assessment students might gain awareness of its benefits because the quality of their work substantially increases due to these means.

Students' self-efficacy may be addressed through instruction. Students could be trained in how to provide and receive proper feedback. Furthermore, students may be trained in suitable platforms that they can use for peer-feedback and self-assessment.

4 CONCLUSION AND OUTLOOK

Competency development on the part of the data clients (students, teachers/tutors, institutions) is a key requirement. Greller and Drachsler (2012, p. 51) have pointed out that the large majority of students currently do not have the required skills to interpret LA results and to determine appropriate next activities. A superficial understanding of data presentation can lead to false conclusions. Furthermore, it is important to understand that data not included in the respective LA approach may be equally if not more important than the data set that is included. To judge a learner's performance merely on one aspect, such as quantitative data provided by a LMS, is like looking at a single piece taken from a larger jigsaw puzzle. Lifelong learning takes place across a wide range of schooling, studying, working, and everyday life situations. In addition to competency requirements, acceptance factors influence the application or decision making that follows an analytics process. Lack of acceptance of analytics systems and processes can lead to blunt rejection of either the results or the suggestions on the part of relevant constituencies (data clients). In order to deal with these issues, future research should focus on empirical evaluation methods of learning analytics tools (Ali et al., 2012; Scheffel, 2014) and on competency models for 'digital learning' (Dawson and Siemens, 2014).

Embedded in our use case, we present two LA measures – technology-supported peer-feedback and self-assessment. They are based on a Student Tuning Model as a continual cycle in which students plan, monitor, and adjust their learning activities (and their understanding of the learning activities) as they engage with LA (Wise et al., 2016). Drawing on a sample of 484 undergraduate students and the TAM, we identified important drivers for students' acceptance. From our point of view, the use case already considers many of these drivers of behavioural intentions. The current course setting includes teamwork in smaller groups. These learner groups can be further supported towards common learning goals, strategies and closer collaboration. Once there is a trusted social group established, a peer-feedback within this group might be better addressed and perceived. For self-assessments, we plan to provide more detailed/customized LA dashboards where learners can set up peer-comparisons based on their learning groups. Our results also lead us to further focus on the appropriate scaffolding on the part of the lecturer, as proposed by Evans (2013). The development of self-assessment skills (and meta-cognitive learning strategies) through LA measures requires close support from the lecturer from the outset.

For a thorough evaluation of our use case, we will survey the students after they will have taken the course. By this means, we want to investigate to what degree we were successful in fostering students' acceptance of peer-feedback and self-assessment. To gain a comprehensive insight, we will also collect qualitative data and evaluate our use case in a mixed methods design.

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