Analysing eCollaboration: Prioritisation of Monitoring Criteria for Learning Analytics in the Virtual Classroom

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Structured Abstract

Purpose – This paper is part of an extensive action research project on learning analytics and focuses on the analysis criteria in Virtual Collaborative Learning (VCL) settings. We analyse how the efficiency of virtual learning facilitation can be increased by (semi-) automated learning analytics. Monitoring items are the starting point that enable the learning facilitator to identify learning problems and deduce adequate actions of intervention. However, the sophisticated media-based learning environment does not allow monitoring of vast amounts of items and appreciate the learning processes simultaneously.

Design/methodology/approach – This paper fulfils the sub-goal of selecting and prioritising monitoring items for e-collaboration. The procedure is split into two Research Questions (RQ). A specification of the monitoring items will be compiled by a comparison and a consolidation of the already existing monitoring sheets. Therefore, we interviewed the responsible docents on differences and similarities. Additionally, we coded each monitoring item inductively due to their monitoring objective. As a result, we reduced the monitoring sheets to 40 final monitoring items (RQ1). In order to prioritise them, the learning facilitators scored the relevance and the complexity of the collection and assessment of data using a questionnaire. The analysis focused on differences in understanding of relevance and complexity. Further, we identified the highest scored monitoring items as well as scores with leverage potential. Afterwards we prioritised the items based on the applied analysis (RQ2).

Originality/value – While previous studies on learning analytics were mostly driven by the educational data mining field and as a consequence had a technological focus. This paper is based on an existing pedagogical concept of VCL and therefore prioritises monitoring items to be implemented as selected learning analytics. Hence, it is guaranteed that the analysis is related directly to the learning content.

Practical implications – This research paper achieved two outcomes: Firstly, a courseindependent standardised monitoring sheet. Thus, the reduction of the monitoring items should simplify and objectify the observation and clarify the performance review. Secondly, an insight into the relevance of each monitoring item had been delivered to the facilitators and provides significance on the quality of e-collaboration. Furthermore, the complexity score shows the necessary effort for data collection and assessment while the combination of relevance and complexity scores leads to the prioritisation of the needs of (semi-) automated learning analytics to support the learning facilitation.

Keywords – learning analytics, eLearning, eTutor, eCollaboration, learning facilitation

Paper type – Academic Research Paper

1 Introduction

The increasing number of students issue a challenge for the education institutes that they meet with eLearning offerings (Bratengeyer et al., 2016, p. 83). Especially modern eLearning courses integrate the students according to a constructivist approach where they have to share and align their individual opinions, experiences and knowledge (Wheeler et al., 2008, p. 987). But the students feel mostly uncertain about this new field of teaching and learning because of rare experiences in (virtual) group work. Thus, it is not sufficient to simply let the students work together. There need to be concrete incentives to support and foster interactions (Murphy, 2004). Thus a transparent communication of the monitoring and grading criteria is suggested at the beginning (Kalb et al., 2011).

For a long period, it remained unclear how to rate the results of online learning, respectively, how the working activities can provide significance on performance and progress (Liang and Creasy, 2004). For several years, approaches in the field of educational data mining and learning analytics were developed to monitor the student activities better. The learning management systems and their databases serve as a basis to reflect and structure these activities. The analyses can be used to measure the success of courses and subsequently derive aspects for improvements (Long and Siemens, 2011) as well as to grade the participants and intervene appropriately (Dawson et al., 2008).

However, previous studies on learning analytics were mostly driven by the informatics and consequently had a technological focus, ignoring the pedagogical demand. So analyses were created which have no specific statement on the status of the learning process (Littleton and Whitelock, 2005). But it needs meaningful and targeted analyses and visualisations to provide users the necessary information for their further actions (Coffrin et al.). This paper is based on an existing pedagogical concept and therefore focusses on monitoring items of an observation sheet. Hence it is guaranteed that the analysis is related directly to the learning content. Unfortunately, the amount of monitoring items cannot be implemented in learning analytics simultaneously. Currently a strategy is missing that recommends the sequence of items for implementation.

Virtual Collaborative Learning

The underlying course setting of the referred observation sheet is a virtual collaborative learning (VCL) project. Herein, interdisciplinary small groups from four to six persons solve complex and authentic, but ill-structured problems. The collaborative group work continues over several weeks and is organised in steps. The courses are split into a couple of tasks that run one after another and in sequence (Balázs, 2005; Tawileh, 2016b). Students are solving the tasks using social software. Therefore, the platform elgg is provided that offers central tools for practicing eCollaboration (see Rietze and Hetmank, 2016; Tawileh, 2016a).

During the course, the participating students are accompanied by eTutors. The eTutors follow the entire process and are available as contact persons if necessary. Beside the passive role of a learning facilitator, the eTutors also have to be active to evaluate the group work and intervene if required. It is necessary for the eTutors to observe the activities of individuals and the group and monitor their interaction and progress. They identify and solve especially start-up difficulties as well as stagnating collaboration (Rietze and Hetmank, 2016). Their actions ensure the success of the learning objectives of the course. These learning objectives address the Bologna goals to improve teaching and learning due to interdisciplinary group work between partners of various countries by using modern information and communication technology. Furthermore, they evolve the ability to compile new connections and develop adaptability, as well as professional competence, team competence, media competence, and intercultural awareness (Bukvova et al., 2006).

Beginning with the analysis of complex tasks and the deduction of subtasks for the group and their group members by the means of the self-initiated search on relevant information for the solution, the meaningful integration of information and the creation, evaluation and deciding of alternatives for a solution through to the presentation and defence of the decisions and proposals for a solution (Rietze and Hetmank, 2016). These learning goals thus focus the analysis, evaluation and creation of knowledge (Anderson and Krathwohl, 2001). Subsequently the learning facilitators and later on the graders cannot concentrate on checking the fact knowledge but rather have to consider the dependences and the contexts of constructing the solution (Rietze and Hetmank, 2016). To assure all these goals and process steps an observation sheet serves as a checklist for the eTutors' work.

2 Research Design

Within an extensive action research project on learning analytics this paper focuses on the monitoring items in VCL settings (Balázs, 2005). We analysed how the efficiency of virtual learning facilitation can be increased by (semi-) automated learning analytics. Monitoring items are the starting point and enable the learning facilitator (lecturers and eTutors) to identify learning problems and deduce adequate actions of intervention. However, the sophisticated media-based learning environment does not allow monitoring the extensive amounts of criteria and appreciate the learning processes simultaneously. Hence an optimal support to succeed the learning objectives cannot be guaranteed by the facilitators (Rietze and Hetmank, 2016). For the purpose of the main project's research objective to ensure qualitative learning facilitation in formal eLearning settings through learning analytics, this paper fulfils the sub-goal of selecting and prioritising monitoring items for eCollaboration. To reach the previously mentioned sub-goal, the following research questions (RQ) will be addressed:

RQ1: Which kind of monitoring determines the quality of eCollaboration?

RQ2: Which necessity needs to be considered when implementing (semi-) automated learning analytics?

The paper focuses on both of these research questions and is thus two-parted. The first part answers RQ1 based on a concrete eLearning arrangement and the respective learning facilitation (paragraph Virtual Collaborative Learning). Hereto, we reduced to original 109 monitoring items of three existing monitoring sheets (state Summer Semester of 2015) to 40 items. The three sheets have been used in courses with comparable learning goals empathising eCollaboration. In a first step, data was collected from responsible lecturers using a group interview to identify and eliminate course specific monitoring criteria. Afterwards the monitoring sheets were further adjusted from 35 duplicates. The remaining monitoring items were analysed based on their content and inductively coded according to their monitored characteristics (Döring and Bortz, 2016, p. 541 pp.). Similar items within a sheet were consolidated before the three sheets were merged. As a result, we created a shortened and simplified list of monitoring items that can be applied course spanning (paragraph Creation of a generalised Monitoring Sheet).

The second part rated the monitoring items from the part before. According to Heinrich et al. (2014, p. 371 p.) we created an online questionnaire with the dimensions 'relevance' and 'complexity'. These two dimensions were rated on a four-step ordinal scale (irrelevant | low relevant | relevant | very relevant respectively simple | low complex | complex | very complex) by eTutors and docents. The characteristic values represent the metric values 1 (irrelevant/simple), 3 (low relevant/low complex), 5 (relevant/complex), and 7 (very relevant/very complex) for further calculations. Beside the content-related questions we gathered the respondents' experiences, the time of the last participation in a VCL as an eTutor or docent, the experiences as a student participant, the course of study, the already achieved or targeted degree of studies, as well as gender. The answers of the socio-demografic data can be seen in Fig. 1. It shows that the majority of the respondents already participated as students (Experiences as a Participant). We can also see that the experiences of a large part were recent (Last participation as an eTutor/Docent). Furthermore, it shows that students of Business Education have the highest count, followed by Business Informatics and students of general Business Administration.

After a pre-test with three test persons we carried out the survey in the timeframe between 05.09.2015 and 07.10.2015. All participants were contacted individually via email and remembered on participation twice. As an incentive, we gave away three Amazon vouchers à 10€. Therefore, the respondents were free to add their contact details to be informed about the potential prize; nevertheless, the questionnaire remained anonymous.

Because of the relative sparse persons who are experienced with the course setting, we contacted nearly the whole population. The exceptions were three eTutors of those we had no contact details. Out of the 48 delivered answers 28 have been completed. The docents reached a participation ratio of 56% (5 of 9), the eTutors reached 43% (23 of 53) (paragraph Scoring of the Monitoring Items).

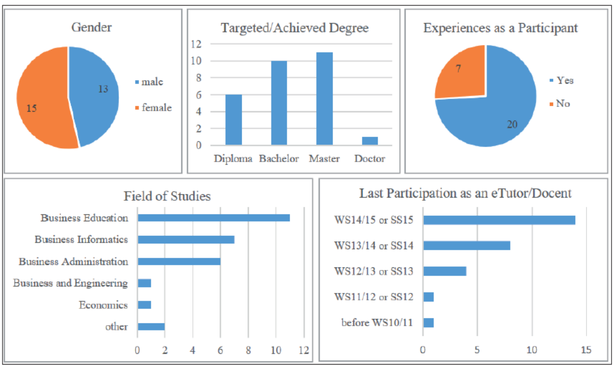

Fig. 1: Results of the socio-demografic data collection

3 Results

Before we focus on the actual content of this paper, the initial situation is elucidated as a basis. An observation sheet serves as a checklist for the learning facilitators to analyse the students' work. The sheets have been applied practically, adjusted demandoriented and improved iteratively by experts over years. Based on the items, the learning facilitator gains an overview of the individual participants and their group work. The items are ascertained manually, rated according to the degree of achievement and annotated with notes. All findings are currently documented in an Excel file. Right now no real-time analysis tool exists to determine the monitoring items more efficiently. A manual monitoring is necessary even though the process is very demanding because of the vast amount of items and can thus be rarely realised simultaneously.

3.1 Creation of a generalised Monitoring Sheet

During the summer semester of 2015 three observation sheets of different docents are used. They are used in three slightly different courses which focus on partially different learning objectives (see paragraph Virtual Collaborative Learning). However, eCollaboration serves group spanning as a learning objective as well as a way of working together to reach all other goals. The courses address different target groups at Bachelor and Master level. Because of these differences the sheets contain 73, 35 and 20 items that are assigned to different monitoring fields.

The objective of a first step of this research is to create a generalised, course spanning monitoring sheet and therefor eliminate the course individual and redundant monitoring items (see chapter Research Design). The result contains a list of forty monitoring items (see Tab. 1) that are grouped by Communication, Teamwork and Result. Thus considering the collaboration process as well as the final product is ensured (column Monitoring Items). To simplify referencing of each monitoring item we introduced abbreviations (column Code). The importance for implementation in learning analytics is mentioned based on three steps of prioritisation whereas 1 means very urgent, 2 urgent and 3 subordinate (column Prio). The reasons for the classification will be explained in the upcoming chapter.

Tab. 1: List of Monitoring Items

Monitoring Items (M)		Code	Prio
Communication	Is the participant actively looking for dialogues with other participants?	C1	3
	Is the participant discussing comments and following up them?	C2	3
	Is the participant stimulating discussions on his/her own contributions?	C3	3
	Is the participant also acting asynchronously (posts in forums etc.)?	C4	1
	Is the participant asking actively if he/she does not understand something?	C5	3
	Is the communication objective and constructive (also in conflicts)?	C6	3
	Is the communication steady and transparent (at absence)?	C7	2
	Is the communication understandable (ideas, proposals)?	C8	
	Is the group communicating to come to an organisational arrangement?	C9	3
Teamwork	Is the participant fulfilling the tasks of his/her role?	T10	3
	Are all tasks completely carried out (overall task, group contract)?	T11	1
	Are subtasks derived from the overall task?	T12	3
	Are subtasks derived transparently from the overall task?	T13	2
	Is the participant encouraging and motivating others for the work?	T14	2
	Is the group working together to find a solution?	T15	3
	Is the group helping each other if needed?	T16	3
	Is the participant undertaking additional tasks actively?	T17	2
	Are the activities of the participant contributing to a common and high qualitative result?	T18	2
Teamwork	Are the activities of the participant reasonable to reach the overall result?	T19	2
	Is the participant referring to others‘ contributions within the solution?	T20	3
	Are various alternatives considered within the solution?	T21	3
	Are decisions made and accepted by the whole group (incl. individual opinions)?	T22	3
	Are decision processes executed structural?	T23	2
	Are decisions reasoned replicable in the documentation of the results?	T24	3
	Is the solution worked out systematically?	T25	3
	In case of crises/problems, which consequences occurred?	T26	2
	In case of crises/problems, were they discussed and solved?	T27	2
	In case of crises/problems, how were they solved?	T28	3
	In case of crises/problems, which cause did they had?	T29	2
	Is the selection of the tools reasonable?	T30	2
Result	Are deadlines adhered (date of delivery, single tasks)?	R31	2
	Is the length adhered (group contract, result, single tasks)?	R32	2
	Is the group contract written detailed and coherent?	R33	1
	Is the elaboration structured logically?	R34	3
	Is the elaboration documented appealingly (group contract, result)?	R35	2
	Is the elaboration documented neatly?	R36	2
	Is the elaboration documented understandable (group contract, result)?	R37	3
	Are references used scientifically sound?	R38	2
	Is the solution qualitative in every detail?	R39	1
	Is the solution fitting to the overall task?	R40	2

3.2 Scoring of the Monitoring Items

To determine the list of priorities of the monitored items, they have been rated by docents and eTutors (see chapter Research Design). Now the results will be analysed to achieve a list of items that should be implemented in learning analytics. The prioritisation takes place according to the importance of the monitoring items, whereas the importance is measured by two dimensions:

- Significance on the quality of eCollaboration (**Relevance**); and
- Effort that is necessary from the beginning at the monitoring and the following abstraction of the monitored content as well as the deduction of feasible actions of interventions (**Complexity**).

Because both of the stakeholders have different views on the monitoring items, they will be asked as independent samples. While a docent takes the role of an administrator of the course and adjusts the monitoring items on the learning objectives and subsequently provides them to the eTutors, they have to operationalise the monitoring items. Hence, the research subjects come from an upper level which aligns the items to the objectives and from the lower level that have experiences from the daily usage. So we can assume that eTutors and docents rate the monitoring items differently. This circumstance in turn derives aspects for prioritisation. They are based on respective extreme values of:

- large differences in understanding of relevance and complexity (**Analysis 1+2**);
- highest relevant and complex monitoring (**Analysis 3**); and
- inefficient monitoring and immediate ability for forecasting (**Analysis 4+5**).

At the end of the survey we received a very small sample size of the docents (n_{Doc}=5) and a small sample size of the eTutors (n_{Tut}=23). These few participants set special requirements for the analysis because the publicly known statistical methods need larger samples sizes. Hence we will use non-parametric methods to analyse the data sets (Bortz et al., 2008, pp. 56–60). The used analysis methods will we explained shortly before the particular paragraph.

Analysis 1: Focus on large Differences in Understanding

As a first aspect we now compare the ratings of relevance and complexity of docents and eTutors. Basically the ratings should be similar to ensure learning facilitation that is aligned with the learning objectives. In case of differences between the both groups the reason can be a missing insight into the intended results and the learning objectives of thecourse. As a consequence, eTutors - as the operative learning facilitators - would not focus on the actually important items but less important ones.

A similar problem occurs if large differences in complexity exist. It could be a sign that docents would face other data than eTutors. This would bias the underlying data collection and would affect the determination of necessary interventions. In an extreme case, reaching the learning objectives could be hindered due to misunderstandings between docents and eTutors.

Subsequently, we analyse if both target groups rate relevance and complexity similar to each other. Instead of the Chi²-Test we use the Freeman-Halton-Test because the sample size is not large enough. It cannot be ensured that 80% of the characteristics have at least five votes and that every characteristic was voted at least once. Even the normal distribution is not guaranteed (Bortz et al., 2008, pp. 94–98). As the results of the Freeman-Halton-Tests we identified the highest differences in relevance at the monitoring items R39 ($p=0{,}05137$), R35 ($p=0{,}1255$), C7 ($p=0{,}1449$), R32 ($p=0{,}1587$) and T11 ($p=0{,}1816$). But we can state a significant difference $\alpha=0{,}1$ only for R39. The distribution of the answers can be seen in Fig. 2, wherein the relative frequencies of the votes for each monitoring item is visualised.

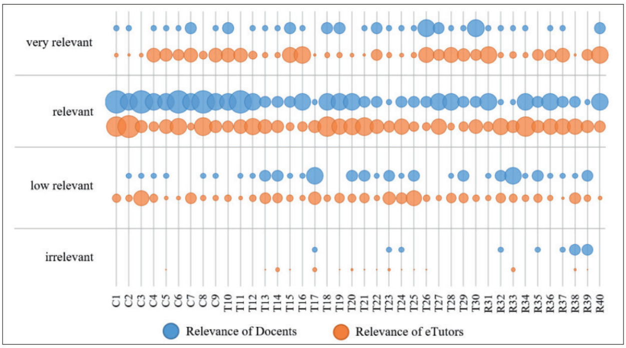

Fig 2: Distribution of Answers on Relevance

Regarding the answers on complexity the highest difference can be seen at the monitoring items C4 ($p=0{,}0422$), T14 ($p=0{,}0422$), T13 ($p=0{,}0737$), R33 ($p=0{,}1224$) and T11 ($p=0{,}1365$). Especially C4, T14 and T13 showing statistically significant ($\alpha=0{,}1$) differences for the effort for processing the relevant data.

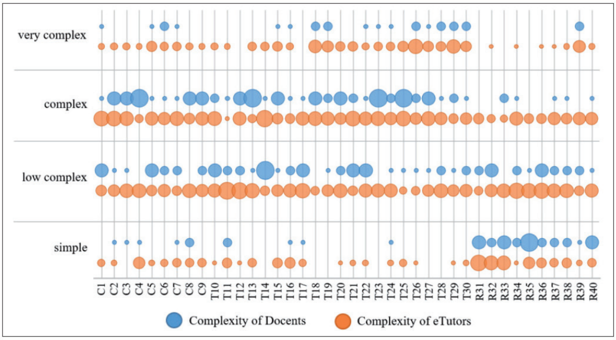

Fig. 3: Distribution of Answers on Complexity

The analysis of different understandings on the monitoring items showed the main disagreements on monitoring items. The reasons should be examined in future. Therefor the implicit concepts of docents on the application and especially the ways of operationalisation through the eTutors should be further analysed. In the end a consensus on the What? (data), Where? (platform/additional data generation), Who? (individual/group) and How? (methods) has to be achieved to objectify the monitoring findings (Rietze, 2016).

Analysis 2: Focus on highest ranked Monitoring Items

Looking at the field in which the target groups have their expertise we use the answers of the docents on relevance and answers of the eTutors on complexity. The points in Fig. 4 represent the averages μ(Complexity of Tut) and μ(Relevance of Docents) of the coded scales (see chapter Research Design) (according to Heinrich et al., 2014, p. 373).

The highest ranked monitoring items are located in the upper right area. To select them, we summarize the belonging averages of the monitoring items.

$$\mathrm{S(M)} = \frac{1}{d}\sum_{D=1}^{d} R(M,D) + \frac{1}{t}\sum_{T=1}^{t} C(M,T)$$

S=Sum, M=Monitoring Item, D=Docent, T=Tutor, R=Relevance, C=Complexity

As the items with the five highest S(M) we identified T26, T18, T19, T27 and T30. These monitoring items produce the highest effort and deliver the maximal evidence on the quality of eCollaboration (**TOP5**).

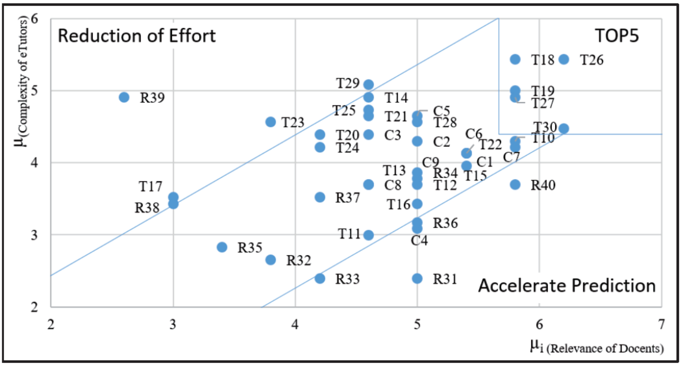

Fig. 4: Ratio of Relevance and Complexity

Analysis 3: Lever Mechanisms

At the same time, Fig. 4 shows observations that are very exhausting but deliver only a minor contribution. These points are located in the upper left side. The eTutors invest much time to monitor while they receive no equivalent benefit. This wastage can be avoided through automatization of monitoring items and thus increasing efficiency of the learning facilitation.

To identify the lever mechanisms, the following formula to calculate the balance of both averages is used:

$$\mathrm{B(M)} = \frac{1}{d}\sum_{D=1}^{d} R(M,D) - \frac{1}{t}\sum_{T=1}^{t} C(M,T)$$

B=Balance, M=Monitoring Item, D=Docent, T=Tutor, R=Relevance, C=Complexity

At first, we focus negative - minimum - values of B(M) that signalised a higher effort than benefit. This is especially relevant for R39, T23, T17, T29 and R38, so they should be automated to avoid the low productive observations (**Reduction of Effort**).

In contrast to these just mentioned monitoring items the opposite area in Fig. 4 shows items with low complexity that are very important to determine the quality. Referred to the formula above, B(M) is maximized and a good prediction can be achieved with low effort. Hereto belong the monitoring items R31, R40, C4, R36 and R33. These observations can be made by eTutors because of their low complexity. But at the same time their easy way to observe and abstract (Bravo et al., 2008) predestines them as first outcomes in learning analytics that can be possibly achieved quickly (**Accelerate Prediction**).

Both minimum and maximum values serve as lever mechanisms for further implementation. While the monitoring items of ‘Reduction of Effort’ are very timeconsuming and complex to determine, an automation would take the time pressure off of the eTutors. The other way around, the items of ‘Accelerate Prediction’ could process the data easily and thus would provide predictions as early as possible.

Summary of Priorities

The chapters above described the various procedures for selecting the monitoring items that should be prioritised in the implementation of learning analytics. Tab. 2 summarizes the five types of TOP5-items. Duplicates are marked bold and should be implemented at first because they address two columns. Afterwards the remaining prioritised – in Tab. 1 as Prio 2 marked – items should be treated. Finally, the unmarked monitoring items should be implemented. The order of the prioritisation is mapped in Tab. 1 in column “Prio”.

Tab 2: List of Prioritised Monitoring Items

Different Understanding of Relevance	Different Understanding of Complexity	Highest Complexity and Relevance	Reduction of Effort	Accelerate Prediction
R39	**C4**	T26	**R39**	R31
R35	T14	T18	T23	R40
C7	T13	T19	T17	**C4**
R32	**R33**	T27	T29	R36
T11	**T11**	T30	R38	**R33**

To avoid misunderstandings, we make aware of the prioritisation that is not exclusively driven by the highest rank in relevance and complexity. Especially the monitoring items with Prio 1 do not fulfil this criterion but rather were selected because of their multiple listing in the above mentioned five analyses.

4 Conclusions

Summarizing the findings of this paper, we achieved two outcomes: Introductory we described the course concept as a basis for the further analyses. Herein we explained the principles of the arrangement and eCollaboration as the central learning objective. As a support of the virtual group work we introduced the eTutors and their observation sheet as a checklist for learning facilitation. The first part of the conducted research consolidated three practical applied observation sheets and standardized them to a course-spanning one that contains 40 monitoring items. Thus the reduction of the monitoring items simplifies and objectifies the facilitation and clarifies the performance review.

Afterwards this observation sheet was sent to eTutors and additional docents who rated the monitoring items due to their relevance and complexity in an online questionnaire. This insight on the one hand provides significance on the quality of eCollaboration and scores the necessary effort for data collection and assessment while the combination of both leads to the prioritisation of the needs of (semi-) automated learning analytics to support the learning facilitation.

The subsequent summary of the conducted analyses prioritised four monitoring items as very urgent und 17 items as urgent for automation. These should be preferred to for further research and the implementation in learning analytics. Hereby the ideas of the docents have to be aligned with the expertise of the eTutors to gather the relevant data. In case of different opinions, they have to be solved consensually to enable an objective evaluation of the situation.

Critically we have to mention the calculation of the ratio of relevance and complexity. Against the statistical rules of analysing ordinal scales based on the median (Kuckartz et al., 2013, pp. 61–67), we have calculated the average to integrate the opinion of the otherwise ignored minority (according to Heinrich et al., 2014, p. 372). Also the dimension 'complexity' just indicates the effort of eTutors to gather information and thus the prioritisation rely on that. The technical complexity of data gathering and processing is not mentioned yet. Especially items that analyse qualitative data are much more difficult to analyse than quantitative ones and mostly need very complex methods (Pozzi et al., 2007, p. 171). First quantitative analyses have already been compiled as a technical feasibility study (Tawileh, 2016a, 2016b) which now have to be integrated demandoriented into the observation sheets. The next steps should evaluate the technical effort for implementing the other monitoring items before a final strategy on learning analytics can be derived.

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