ABSTRACT
While there is currently much buzz about the new field of learning analytics and the potential it holds for benefiting teaching and learning, there is also much uncertainty and hesitation, even extending to skepticism. A clear common understanding and vision for the domain has not formed yet among the educator community. A survey among educational practitioners and researchers with 156 participants from 31 countries revealed substantial uncertainties and relatively low confidence levels, paired with high expectations and wishful thinking.

The following article presents the results of this learning analytics survey that had been distributed in September 2011 to an international audience from different sectors of education. The questionnaire was designed around a conceptual framework for learning analytics and aimed at extracting the expectations and confidence levels of stakeholders in the six domains of the framework.

In the article, we first briefly introduce the learning analytics framework and its six domains that formed the backbone structure to our survey. Afterwards, we describe the method and key results of the learning analytics questionnaire and draw further conclusions for the field in research and practice. The article finishes with plans for future research on the questionnaire and the publication of both data and the questions for others to utilise.

Categories and Subject Descriptors

General Terms

Keywords
Learning analytics, confidence survey, expectations, privacy, learning technologies, innovation.

1. INTRODUCTION
In a submitted article to the special issue on learning analytics [5], we developed the idea of a conceptual framework encapsulating the design requirements for the practical application of learning analytics. The framework models the domain in six critical dimensions, each of which is subdivided into sub-dimensions or instantiations. Figure 1. below graphically represents the framework:

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comprehensive the framework is in this respect. In case the former condition would prove true, this could possibly require an adaptation of the model to map onto this emergent understanding. However, if false, this may also lead to adaptation, but in a different direction, by way of being even more inclusive for diversity than now.

In each of the dimensions of the framework, concrete aspects were taken into focus by the questionnaire in the following way: The stakeholders dimension looked into expected beneficiaries; objectives tried to highlight the preference between reflective use of analytics and prediction; It also checked for the development areas where benefits are most likely or are expected; the data section looked into stances on sharing and access to datasets; methods investigated trust in technology and algorithmic approaches; constraints asked for observations on ethical and privacy limitations (so-called soft-barriers); and, finally, competences looked into the confidence for exploiting the results of analytics in beneficial ways.

Although we won’t go into this issue in this article, we are aware that there may be cultural differences that influence the subjective evaluation of the dimensions of learning analytics.

In section two below, we go on to describe in more detail the set-up of the questionnaire, the participants and the distribution method. In section three, we present and discuss results and statistical effects.

2. EMPIRICAL APPROACH

2.1 Instrument

To evaluate the perception and confidence of the stakeholders in learning analytics, we developed a questionnaire that builds upon the six critical dimensions (see above) and implicitly evaluates their validity. For each dimension, we asked the participants two questions and offered the opportunity for open comments. Questions were formulated in a variety of modes, including prioritisation lists, Likert scales, matrices, and decision questions.

In order to reach a wide network of a globally distributed community, we designed and hosted the questionnaire online, using the free limited version of Qualtrics (qualtrics.com). This tool is pleasantly designed and easy to use. It provides several sophisticated question-answer types with more being available for premium users. The data and the questionnaire are exportable in a number of popular formats including MS Excel and SPSS. The free version came with a limitation of 250 responses. All excess answers were recorded, but discarded in the analysis and data export. In our case, with a small sampling community, the free version proved to be sufficient.

2.2 Reach

We first promoted the questionnaire in a learning analytics seminar at the Dutch SURF foundation, a national body for driving innovation in education in the Netherlands. We then went on to distribute the questionnaire through the JISC network in the UK and via social media channels of relevant networks like the Google group on learning analytics, the SIG dataTEL at TELEurope, the Adaptive Hypermedia and the Dutch computer science (SIKS) mailing lists and to participants in international massive open online courses (MOOCs) in technology enhanced learning (TEL) using social network channels like facebook, twitter, LinkedIn, and XING. This distribution method is reflected in the constituency reached, in that there is, for example, a limited response rate from Romance countries (France, Iberia, Latin America) against a high return from Anglo-Saxon countries. The survey was available for four weeks, during September 2011. After removal of invalid responses we analysed answers from 156 participants, with 121 people (78%) completing the survey in full. In total, the survey now covers responses from 31 countries, with the highest concentrations in the UK (38), the US (30), and the Netherlands (22) (see Figure 2. below).

![Figure 2. Geographic distribution of responses](image)

2.3 Participants

Although we tried to promote the questionnaire equally to schools, universities and other education sectors, including e-learning companies, we received a significantly higher response from the tertiary sector (further and higher education) with 74% (n=116). It is probably fair to say that learning analytics as a topic is not yet popular or well-known in other educational sectors with the combined K-12 sector amounting to 9% (n=13) and some 11% (n=17) coming from the adult, vocational, and commercial sectors. The remaining 6% (n=9) in the ‘other’ subgroup includes cross-sector and other individuals, such as retirees from the education sector.

The only other demographic information we collected from participants was their role in the home institution. Here we received a broad variety of stakeholder groups that deal with learning analytics. Multiple answers were possible, taking into account that people may have more than one role in their organisation.

The three largest groups of our test sample were teachers with 44% (n=68), followed by researchers with 36% (n=56) and learning designers with 26% (n=41). With 16.1% (n=32) senior managers too were identified as a representative group of which two thirds (65.6%) came from HE institutions. 40.4% of the 156 participants claimed more than one role in their institution, of which again 40.3% were teacher/researchers (16.7% of the total sample).

Next, we present the most relevant results from the online questionnaire regarding expectations and confidence in learning analytics.

3. RESULTS

Our report on the results is organized along the lines of the six dimensions of the learning analytics framework (cf. section 1 above). We paid special attention to mapping opinions against institutional roles in order to identify any significant agreement or discord in each of the dimensions.
One uncertainty underlying the outcomes is the lack of an established domain definition and/or established domain boundaries through practice. The term “learning analytics” is still rather vague, shared practice in the area is only just emerging and a scientifically agreed definition lacking. From ongoing research and development work we know that some researchers subsume for example educational business analysis or academic analytics [8], or action analytics [7] under learning analytics [2]. Thus, the domain name itself carries a highly subjective interpretation, which almost certainly influenced the answers in the survey. We have no doubt that as the domain matures further, this interpretation will be narrowed down, leading to a better graspable scope and possibly more congruencies in the responses.

3.1 Stakeholders

In this section, we wanted to know: (a) who was expected to benefit the most from learning analytics, and, (b) how much will learning analytics influence specific bilateral relationships?

Regarding the prioritisation of the stakeholder of learning analytics, the majority of respondents agreed that learners and teachers were the main beneficiaries of learning analytics. The weighting of the 155 responses shows that learners were rated highest at 1.9 mean rank, followed by teachers with 2.1. However, the ranking distribution and standard deviation for learners was higher (1.12) than for teachers (0.88). Institutions came in third place with an average rank of 2.6. There was also substantial contribution to the ‘other’ category with suggestions for further beneficiaries. Among those and most prominent were government and funding bodies, but also employers and support staff were mentioned.

Graph 1. Relationships affected (1)

Graph 1 above illustrates the outcomes of question (b) and confirms the findings of question (a) above. The peaks identify the anticipated intensity of the relationship. Relationships with parents are not seen as majorly impacted, which is probably due to the fading influence parents have in tertiary education. It would be interesting to complete this picture with more responses from the K-12 domain. The highest impact is seen in the teacher - student relationship (83.5%, n=111, of respondents emphasised this), whereas the reverse student - teacher connection is strengthened slightly less (63.2%, n=84). Only less than half the participants see peer relationships as being strengthened through learning analytics: learner - learner by 45.9% (n=61), and teacher - teacher by 41.4% (n=55). At roughly the same level comes the relationship between institution and teachers (46.6%, n=62).

Graph 2. Relationships affected (2)

In the spider diagram (graph 2 above), the area indicates that it is the relationships of teachers that are expected to be most widely affected, followed by learners, institutions, and parents at a minimal level.

3.2 Objectives

In this section, we asked participants in which way learning analytics will change educational practice in particular areas. Of the total answers given in all areas (n=1543), collected from 119 participants, only 10.8% of responses anticipated no change at all. On the other hand, the remaining responses left it open whether the expected changes will be small (43.8%) or extensive (45.4%).

Graph 3. Objectives for learning analytics

Looking at the individual areas (cf. graph 3 above), the highest impact was expected in more timely information about the learning progress (item 2), and better insight by institutions on what’s happening in a course (item 8). On the bottom end were expectations with respect to assessment and grading (items 6 and 5), where the least changes were anticipated.

Further, we contrasted the importance of three generic objectives for learning analytics: (a) reflection, (b) prediction, (c) unveil hidden information. 47% (n=61) of the respondents felt that stimulating reflection in stakeholders about their own performance was the most important goal to achieve, while 37% (n=48) expressed the hope that learning analytics would unveil hidden information about learners. Both are not necessarily in contradiction to each other, since insights into new information can be seen as motivator for reflection. However the case may be, only 16% (n=20) favoured the prediction of a learner’s performance or adaptive support as a key objective.
When looking at these objectives from the perspective of the different roles of participants, we find that teachers show a fairly equal interest in unveiling hidden information 44.6% (n=25), and in reflection 37.5% (n=21). This is a reasonable finding as many teachers expect learning analytics to support them in their daily teaching practice by offering additional indicators that go beyond reflection processes. On the other hand, 60.4% (n=29) of researchers indicated a clear preference for reflection.

Translated into technological development, the expectations favoured more adaptive systems (highest rank), followed by data visualisations of learning, and better content recommendations in third place. Further interesting suggestions were “learning paths/styles adopted by students”, the clustering of learning types, and applications for the acknowledgement of prior learning.

A further question surveyed the perception of learning analytics being a formal or less-formal instrument for institutions. In two intermixed sets of three options, one set represented formal institutional criteria: mainstream activities, standards, and quality assurance, all relating to typically tightly integrated domains that are governed by institutional business processes and strategies. The other set contained three less-formal and less monitored areas of pedagogic creativity, innovation, and educational experimentation. All three items represented individual choice of staff members to be innovative, experimental, and creative in their lesson planning and teaching activities. As indicated in graph 5 below, among the 129 responses, there was a noticeable preference towards less formal institutional use of learning analytics at a cumulative ratio of 55:45 percent. Quality assurance ranked highest in importance among the formal criteria, whereas innovation was seen as most important aspect of all criteria.

Graph 4. Generic preference

Graph 5. Formality versus innovation

One participant summed up the situation of these findings in the following statement: “It would be easy for learning analytics to become a numbers game focused on QA, training/instruction and rankings charts, so promoting its creative and adaptive potential for lifelong HE/professional-life learning is going to be key for the sector - unless learning analytics people want to spend all their lives doing statistical analysis.”

3.3 Educational data

The section on data investigated the parameters for sharing datasets in and across institutions. The potential of shareable educational datasets as benchmarking tools for Technology Enhanced Learning is explicitly addressed by the Special Interest Group (SIG) dataTEL of the European Association of Technology Enhanced Learning (EATEL) and has been demonstrated in [11]. Sharing of learning analytics data is impeded by the lack of some standard features and attributes that allows the re-use and re-interpretation of data and their applied algorithms [3]. For researchers, the most important feature was the availability of added context information (n=43, means 3.42). Perhaps, equally unsurprising was that for the manager group sharing within the institution (n=16, means 3.63) and anonymisation (n=19, means 3.53) were the most important values. Teachers, on the other hand, valued context (n=52, means 3.42) and meta-information (n=47 means 3.47) the most. At the other end of the spectrum, version control was the least important attribute across all constituencies (n=106, means 2.93). However, despite ‘version control of educational datasets’ was ranked lowest, we still believe that this will play an important role in an educational data future. Version controlled datasets will offer additional insights into reflection and improvements through learning analytics by comparing older and newer datasets.

Graph 6 illustrates the importance of the given data attributes. Note that the notion of “important” outweighs the “highly important” overall, which results in a lower means value.

Graph 6. Data attributes

To get an idea of existing educational data, we asked participants about their institutional IT systems. For learning analytics, the landscape of data systems will play an important part in information sharing and comparison between institutions.

In the tertiary education sector alone (Further and Higher Education), 93.9% (n=92) reported an institutional learning management system, which made this the most popular data platform by far. This was followed by a student information system 62.2% (n=61) and the use of third-party services such as Google Docs or Facebook 53.1% (n=52). Table 1 below shows a summary inventory of institutional systems in use across all sectors of education covered in our demographics.

We assume that the more widely available a type of system is, the more potential it would hold for inter-institutional sharing of data, which could be utilised for comparison of educational practices or success factors. However, such sharing would depend on the
willingness of institutions to share educational datasets with each other. When asked this question, a majority of people (86.6%, n=71) were happy to share data when anonymised according to standard principles.

Table 1. Data systems

<table>
<thead>
<tr>
<th>Answer</th>
<th>Response</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning management system (e.g., Blackboard, Moodle)</td>
<td>111</td>
<td>89%</td>
</tr>
<tr>
<td>Student information system</td>
<td>73</td>
<td>58%</td>
</tr>
<tr>
<td>External services (e.g., Google docs, Facebook, Twitter, slideshare, iTunes U)</td>
<td>64</td>
<td>51%</td>
</tr>
<tr>
<td>Intranet</td>
<td>55</td>
<td>44%</td>
</tr>
<tr>
<td>Wild platform</td>
<td>47</td>
<td>38%</td>
</tr>
<tr>
<td>Course management system</td>
<td>45</td>
<td>36%</td>
</tr>
<tr>
<td>Social networking platform</td>
<td>44</td>
<td>35%</td>
</tr>
<tr>
<td>E-portfolio system (e.g., Mahara)</td>
<td>42</td>
<td>34%</td>
</tr>
<tr>
<td>Mobile platform (e.g., Apps, e-books)</td>
<td>36</td>
<td>29%</td>
</tr>
<tr>
<td>other (please specify)</td>
<td>8</td>
<td>6%</td>
</tr>
<tr>
<td>Sensor data (e.g., location data)</td>
<td>5</td>
<td>4%</td>
</tr>
</tbody>
</table>

What is slightly contradictory is that people who indicated before that anonymisation was not an important attribute for data are less inclined to share (n=18, 83.3% yes : 16.7% no) than people who felt that it was highly important (n=40, 92.5% yes : 7.5% no).

3.4 Methods

Learning analytics is based on algorithms (formulas), methods, and theories that translate data into meaningful information. Because these methods involve bias [1], the questionnaire investigated the trust people put into a quantitative analysis and in accurate and appropriate results. Over all, the responses were located at mid-range between no confidence and total confidence. Among the given choices, slightly higher trust was placed on the prediction of relevant learning resources. This may be due in analogy to the amazon.com recommendation model, which is well-known and widely trusted. Other recommendations, such as predictions on peers or performance were rated rather low.

What seems interesting to us is that the widely interpretable hope for a comprehensive view on learning progress was given the highest confidence, but perhaps this shows wishful thinking rather than a real expectation. The percentage on the horizontal axis in the graph below shows the level of confidence.

Graph 7. Confidence in accuracy

One comment criticised that it was “disappointing that you included institutional markers, rather than personal ones for the learners, e.g. while learning outside the institution, which in my view are much more important and interesting”. We are not aware that the questions actually reflected an institution-centric perspective. At the same time, we still remain sceptical that analytics might currently be able to seamlessly capture learning in a distributed open environment, but mash-up personal learning environments are on the rise [12] and may soon provide suitable opportunities for personal learning analytics as has recently been presented in [6], and [9].

3.5 Constraints

The constraints section focuses on the mutual impact that wider use of learning analytics may have on a variety of soft barriers like privacy, ethics, data ownership, data openness, and transparency of education (see graph 8 below). It should provide more detailed information on potential restrictions or limitations for the anticipated benefits of learning analytics. Most of the participants agree that learning analytics will have some or very much influence on the mentioned characteristics. Only a few did not expect any effects on privacy (10.4%, n=96) and ethics (8.8%, n=102). The majority of the responses believe that learning analytics will have the biggest impact on data ownership (66.4%, n=107) and data openness (63%, n=108) followed by more transparency of education (61.3%, n=111).

Graph 8. Problem areas of learning analytics

After the general weighting of the expected impact on these constraints, we explicitly asked the participants how they estimated the influence of learning analytics and automated data gathering on the privacy rights of individuals by further describing what we mean with privacy rights in four statements (see graph 9 below).

From 123 responses it appears that there is much uncertainty about the influence of learning analytics on privacy rights (cf. graph 9). The answers are widely spread from ‘no effect at all’ until ‘very much effect’. But the majority of participants believe that learning analytics will influence all four privacy dimensions at least a little. By recoding the given answers into a negative voting (will have no effect) and a positive voting (will have an effect) we got a clearer picture of the expectations of the participants. Regarding statement 1, about two thirds (65.8%, n=81) believe that learning analytics will affect ‘privacy and personal affairs’. Equally, in statement 3 - ‘ownership and intellectual property rights’ - we can again see a clear majority (60.1%, n=74) convinced that these will be affected by learning analytics. Statement 2 - ‘Ethical principle, sex, political and
To get further information on these pressing soft barriers, we wanted to know if the participants have already (a) an ethical board and guidelines that regulate the use of student data for research. Further, we wanted to know (b) if they trust anonymisation technologies, and finally (c) how they rate a concrete example for data access in their own organisation to test the two answers before.

Regarding (a), the majority of the participants 61% (n=75) indicated that they have an ethical board in place. Another 18% (n=22) said that they did not have such a body in place, whereas 21% (n=26) were unsure. Yet to us, such an organisational infrastructure represents an important starting point for more extended learning analytics research that is ethically backed up through proper procedure.

With respect to (b), we went on to ask the participants whether thought a (national) standard anonymisation process would alleviate fears of data abuse. With 49% (n=60), the majority of the 123 participants showed high trust in anonymisation technologies, whereas 24% (n=29) did not believe that anonymisation would be effective to reduce data abuse. 21% (n=26) indicated they know too little to answer this question. This leads us to the interpretation that in case learning analytics utilises data that is protected by legislation, participants expect further development of effective anonymisation techniques to deal with this issue.

After having asked participants about ethical guidance and their trust in anonymisation, we tested with question (c) how the participants estimated the use of educational data within their organisation. We asked them whether institutions should allow every staff member to view student data internally in the organisation. In this, we received a significant negative response from the participants. 43% (n=53) did not want to allow all staff members to view student data, only 30% (n=37) did not see any problem with shared access. We also received 15% open text responses to this question that mainly emphasised the need for leveled access to student data in compliance with the law and ethical regulation and the strong need to anonymise data. The tenor in the comments strongly pointed to a “need to know” rational. That is to say that participants felt that only people who had good reasons to see such data should be permitted to access them. As one commentary phrased it: “Only if legitimately necessary and only for those who have a need to know”.

To sum up the results of the constraints section, we found that many organisations have ethical boards and guidelines in place. A large number of respondents trust that anonymisation of educational data is possible but not necessarily sufficient to enable full internal exploitation of the educational data within an organisation.

3.6 Competences

In our section on the competences dimension, we wanted to identify the key competences connected with learning analytics. We also asked for the confidence experts have in the independence of learners to exploit learning analytics for their own benefit.

According to the learning analytics framework we suggested the following seven key skills: 1. Numerical skills, 2. IT literacy, 3. Critical reflection, 4. Evaluation skills, 5. Ethical skills, 6. Analytical skills, 7. Self-directedness. We wanted to know which of these skills the participants find important to benefit from learning analytics? Graph 10 shows the spider diagram of the answers.

The participants found all mentioned skills rather important for learning analytics. By way of means ranking, participants identified self-directedness (means 3.53) and critical reflection (means 3.42) as the most important competences required from beneficiaries. These were rated as ‘highly important’ by 59.3% (n=67) and 48.7% (n=57) respectively. Numerical skills (means 2.83) and ethical thinking (means 2.95) were on the bottom end of the scale. We consider this in line with the previous answers to ethical aspects of learning analytics.

In addition to the required skills, we wanted to know whether participants thought that learners were competent enough to independently learn from learning analytics reports? It turned out that a significant majority did not think that learners would be able to deal with learning analytics reports without additional support (70.2%, n=85). Only 21% (n=26) believed that learners were competent enough to do so. We have to admit that we did not ask the same question with respect to skills required of teachers. This would have been an interesting comparison at this point.

In conclusion of this section we can say, that the results suggest that there is little faith that learning analytics will lead to more independence of learners to control and manage their learning process. This identifies a clear need to guide students to more self-
directedness and critical reflection if learning analytics should be applied more broadly in education. This interpretation is quite in contrast with some suggestions made with respect to empowerment of learners through providing graphical reflection of the learning process and further access to additional information regarding their learning progress [4].

4. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH
The current article reported the results of a learning analytics survey that aimed at extracting the expectations and confidence levels of stakeholders in the six domains of the learning analytics framework. In this part, we summarise the major findings regarding the six dimensions of the framework.

Participants identified the main beneficiaries in learning analytics as learners and teachers followed by organisations. Furthermore, the majority of respondents agreed that the biggest benefits would be gained in the teacher-to-student relationship and that learners would almost certainly require teacher help to learn from an analysis and for taking the right course of action. This is rather surprising as learning analytics is seen by many researchers as an innovative liberating force that would be able to change traditional learning settings by reflection and peer support, thus strengthening independent and lifelong learning. This latter opinion on independence could be seen in the ‘objective’ section of the survey (cf. chapter 3.2 above) where the majority expressed a preference for learning analytics to pay special attention to non-formalised and innovative ways of teaching and learning. Yet, respondents expect less potential impact on the student-to-student and the teacher-to-student relationships. This current perspective may be affected by the scarcity of learning analytics applications that demonstrate the innovative possibilities for learning and teaching. Thus people may not have a clear point of reference as, for example, is the case for ‘social networks’ where an established group of competitive platforms exists.

Further under chapter 3.2, the survey concludes that research on learning analytics should focus mainly on reflection support. The questionnaire results clearly emphasised the importance of ‘stimulating reflection in the stakeholders about their own performance’. This goal could be supported by revealing hitherto hidden information about learners, which was the second most important objective. It then surprised us not to find the stimulation of learner reflection top of the list in the detailed objectives’ list where it was ranked only fourth behind more timely information, institutional insights, and insights into the learning context.

Our institutional inventory in chapter 3.3 gives an overview of the most widespread IT systems. These could be prioritised by learning analytics technologies to gain the biggest impact. They also provide the best ground for inter-institutional data sharing. Anonymisation can perhaps be seen as the most important enabler for such sharing to happen. It is emphasised in a number of responses as the second most important data attribute and confirmed in the willingness of people to share if data is anonymised. For a clear majority anonymisation also reduces fears of privacy breaches through sharing (cf. chapter 3.5). On the other hand, when it comes to internal sharing with departments and operations’ units of the same institution, the use of available data will continue to be an uphill struggle, and, according to participants, require good justification. Here, perhaps, a clearer mandate to ethical boards may help. These are already widely in place.

Chapter 3.4 on methods revealed that trust in learning analytics algorithms and is not well developed. We interpret the mid-range return levels as a slight scepticism towards “calculating” education and learning. Still, there is an expressed hope that a more comprehensive view on learning could be facilitated. We would have to wait and see to what extent this can be realised.

Overall rather low was the expectations of impact on assessment. A majority of people did not see easier or more objective assessments coming out of learning analytics (cf. chapter 3.2). They were also not fully convinced that it would provide a good assessment of a learner’s state of knowledge (cf. chapter 3.4).

A large proportion of respondents thought learning analytics may lead to breaches of privacy and intrusion. Yet, they ranked privacy and ethical aspects as of lesser importance to consider (cf. chapter 3.5) or for further competence development (cf. chapter 3.6). However, data ownership was expressed as highly important. This may be interpreted in that way that if ownership of data lies with the learners themselves, there is no perceived risk for privacy or ethics.

In the area of competences, participants mainly stressed the importance of self-directedness, critical reflection, analytic skills, and evaluation skills. On the other hand, few believe that students already possess these skills. This indicates to us a need to support students in developing these learning analytics competences.

We are aware of several limitations to both the questionnaire and the presented results. As has been mentioned in the introduction, there is a dominance of responses from the Higher Education sector that makes the study only partly representative for other educational domains. Another limitation is the virtual absence of students (undergraduate or secondary) although we did receive a tiny fraction of responses from lifelong learners. This makes the results of the survey biased towards a top-down perspective on learning analytics. Furthermore, the survey only represents a select few Western cultures. We need to be aware that substantial differences exist in educational cultures and that learning is always local. It would perhaps provide for interesting future research to compare these results with other dominant education cultures.

One hopefully time-restricted limitation is the low awareness of learning analytics among the target survey group and learners especially. With the rise of useful and popular learning analytics applications, we hope that this limitation will ease away over time and thus yield more concrete insights into the field of confidence in learning analytics. As such, this survey can only be taken as an indicative insight of innovators and early adopters.

To address these limitations and to gain more valid insights into confidence in learning analytics we intend to do further research and plan to target the K-12 and adult education sector more specifically. Additionally, investigating the student perspective more intensely might reveal interesting contrasts to the above reports.

After collecting a more representative dataset, we plan to apply more advanced analysis methods like the Group Concept Mapping [10] to further analyse the stakeholder groups and to identify consensus about particular issues in learning analytics among them. Group Concept Mapping will allow identifying thematic groups within learning analytics and it allows making a clear distinction between different aspects of learning analytics.
Finally, we want to announce that the underlying datasets of this article and the planned extended version of this dataset will be made publicly available at the datacite.org repository with the acceptance of this article. In that way, we would like to encourage the learning analytics community to gain additional insights from our dataset for the fast evolving of the learning analytics research topic.

5. ACKNOWLEDGMENTS
We would like to thank all participants in the survey and those who further disseminated it to their networks. Further, we want to thank the NeLLLI funding body and the AlterEgo project that sponsored part of the authors’ efforts.

6. REFERENCES