Stakeholder Responsibility for Building Trustworthy Learning Analytics in the AI-Era

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Abstract: This position paper builds on previous research publications and activities related to trustworthy learning analytics (LA) to provide an additional angle on the fundamental considerations for ensuring trustworthy LA. In our view, these considerations include strategic guidance and support, pedagogical soundness and human interaction, stakeholder engagement, data and AI literacy, ethics, data limitations and meaningful use of algorithms, as well as transparency of the whole process. In this paper, we discuss each of the considerations with respect to the roles and responsibilities of the key stakeholders in the LA systems: educational leaders, educators (especially teachers) and students.

1 INTRODUCTION

It is widely known that the digital age has brought numerous changes to teaching and learning, and educators and students alike use digital tools and artificial intelligence (AI) to support and enhance learning on a daily basis. One of the most advanced ways of harnessing technology to foster learning is the use of learning analytics (LA) to better understand learning, provide targeted learning support, improve the quality of learning experiences, and encourage self-regulated learning. However, while during the last decade the potentials and benefits of LA have been widely recognized in research as well as educational practice, especially in higher education, its use is still far from widespread (Tsai et al., 2021). There is, clearly, a whole range of context-specific reasons for that, which has been addressed in LA research (Tsai & Gasevic, 2017).

What has been standing out as one of the significant factors possibly affecting the adoption of LA is trust (Tsai et al., 2021). In some of the first

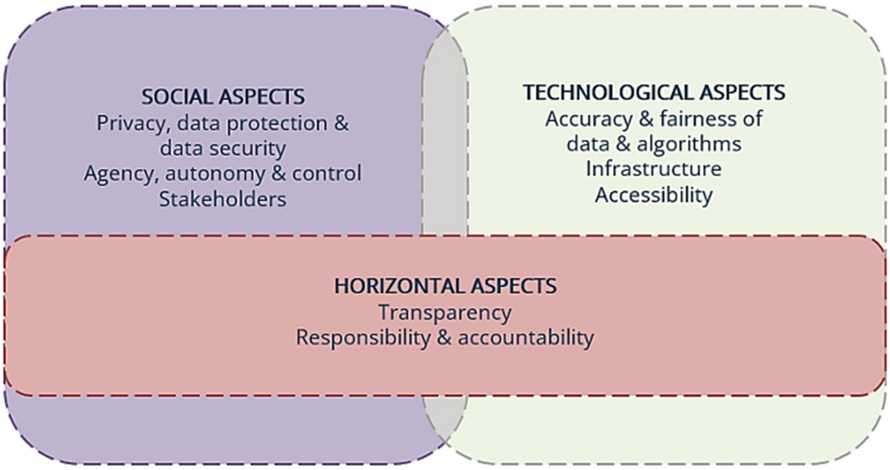

Figure 1: Aspects and dimensions of trustworthy LA (from: Svetec & Divjak, 2025).

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attempts to define trust in the context of LA, it has been described as "subjective, psycho-social, relational and often asymmetrical and founded on the character/values/credibility and track record/consistency/expertise of the person/organization requiring our trust" (Slade et al., 2023). It should be noted, though, that trust and trustworthiness are not synonymous. In this paper, we look at trust as a subjective belief, while we consider trustworthiness as a more measurable "quality of LA which abides by legal rules and ethical principles related to learners' privacy, their data security and control, is based on non-biased data and algorithms, transparently used, and can be trusted to support all learners in successful acquisition of learning outcomes" (Svetec & Divjak, 2025).

Against the described background, and especially since LA is "increasingly unthinkable without AI" (Slade et al., 2023), the issue of trustworthiness of LA has been high on the agenda in LA research. With parallels to trustworthy AI, comparable aspects of trustworthy LA have been explored and discussed (Figure 1). Some of those aspects are more social, including ethical concerns related to (primarily students' and educators') privacy, data protection and security, their agency, autonomy, and control pertaining to the collection and use of data, as well as trust in stakeholders' competences and interests. Others are more technological, referring to data and algorithms and the way they affect accuracy and fairness of LA, as well as the need for appropriate infrastructure and accessibility. Horizontally, there is a need for transparency, not only in terms of data collection, but also interpretability and explainability of algorithms. Another essential aspect is assuming responsibility and ensuring accountability, at institutional and higher levels, in terms of leadership and policy supporting implementation of LA that considers all the other aspects of trustworthiness. (Svetec & Divjak, 2025)

With this position paper, our aim is to contribute to the debate on trustworthy LA by discussing what educational systems, institutions and individuals can do to support trustworthy and trusted implementation of LA.

2 COLLECTION OF INSIGHTS

Besides the authors' current informed positions, this position paper takes into account the discussions among experts and researchers previously held in an international context. First, the paper builds on the insights from a panel discussion organized within the *Learning Analytics in Practice 2024* conference, held online worldwide in June 2024, which gathered four esteemed LA experts from Europe and Australia. Second, the paper presents the highlights of a workshop and three focus groups on trustworthy LA held as part of the *Trustworthy Learning Analytics and Artificial Intelligence for Sound Learning Design* (TRUELA) project. The workshop was held in March 2024 and included eight LA experts and seven HE educators, and focus groups were held in September 2024, with 18 participants from Europe and South Africa.

3 FUNDAMENTAL CONSIDERATIONS FOR BUILDING TRUSTWORTHY LA SYSTEMS

Strategic Guidance and Support Are Indispensable. Research has established there is a lack of institutional policies for the implementation of LA (Baker et al., 2021; Ifenthaler et al., 2021; Vigentini et al., 2020). However, it is important to make strategic-level decisions and develop clear policies on the use of educational data: what data to collect, what to monitor and what to do with the findings (Rienties, 2021; Rienties & Herodotou, 2022). Being clear about the strategy may also contribute to the motivation of individuals to consent to share their data and participate in LA. Besides developing policies and strategies, educational institutions should engage in sharing information and educating everyone involved in LA, for example, through teacher training. Institutions should also provide encouragement, supporting champions to experiment and inspire others, as well as fostering interdisciplinarity and links between research and practice (Herodotou et al., 2020; Kaveri et al., 2023). Finally, it is essential that institutions ensure the necessary financing for the implementation of LA, including infrastructure and training, and invest in explainable LA systems.

Pedagogical Soundness and Human Interaction Remain the Backbone. Only meaningful LA should be trusted. For LA to be meaningful, it is important to ensure a sound pedagogical foundation and enable theoretical and practical educational (didactical) explainability of LA. Furthermore, while LA systems provide visualizations and reports, however rich and meaningful, these only achieve their purpose if they are reacted upon, interpreted and if improvement is considered (Alcock et al., 2024; Clow, 2012; Herodotou et al., 2023; Kaliisa et al., 2024; Muukkonen et al., 2023). Here, teachers remain central. They are the ones who should consider the insights from aggregated data, but keep the individual approach to their students, supporting them in more successful learning. While we agree that teachers are essential for trust-building, over 10 years of research at the Open University with large-scale adoption of LA dashboards suggest that less than half of teachers regularly use these kinds of dashboard (Herodotou et al., 2020, 2023). In part teachers who are less likely to use these LA systems indicate that they need more support and training to use these complex and data-driven systems, but also there is an underlying concern around whether (or not) the data can be trusted, and what the most appropriate intervention strategies might be (Frank et al., 2016; Herodotou et al., 2023).

Engaging Stakeholders Can Enhance Meaningfulness and Trust. In the last couple of years, there has been quite some discussion on human-centered LA. This refers to involving educational stakeholders in the process of designing and evaluating LA systems, as well as studying the sociotechnical factors that affect the success of LA (Alcock et al., 2024; Buckingham Shum et al., 2019; Buckingham Shum et al., 2024). Engaging LA users - primarily teachers, other educators and students - in LA development and implementation can help understand their needs to provide meaningful LA on the one hand, and enable them to understand how LA helps them on the other hand (Gedrimiene et al., 2023). Knowing why they are providing their data may increase stakeholders' motivation to participate and support their trust in LA.

Data and AI Literacy Are the Foundation. Stakeholders do not always understand LA (Herodotou et al., 2020, 2023), which may make it hard for them to trust it, and subsequently use it. To be able to trust LA, it is important to understand data, know how to use appropriate methods of analysis, and interpret the results (Gedrimiene et al., 2023). This could be supported with the use of AI, including in terms of providing suggestions and recommendations for improvements. For example, several fitness apps (e.g., Strava) provide people with detailed training data on their phone after they went for a run or a cycle. These apps provide very rich and dynamic data of a particular work-out but do require substantial data skills and understanding to make sense of whether or not a person has benefited from a particular training. Recently, some apps have made Generative AI (GenAI) advice available based upon months of data of a user, which beyond an easy to follow narrative of the actual workout also provides suggestions of further training. By combining months of data with easy storytelling this GenAI might be more attractive for some users. However, the use of AI should be approached with caution, especially when it comes to the interpretation of mathematical and statistical models. When interpreting LA results, it is also essential to be mindful of differences in learning contexts, learning dispositions and cultural perspectives.

Ethics Is the Cornerstone. Adequate privacy, data protection and security arrangements (Slade & Prinsloo, 2013; Tzimas & Demetriadis, 2021; Ungerer & Slade, 2022), aligned with the relevant regulation, are paramount. Stakeholders need to be allowed agency, autonomy, and control when it comes to the use of their data (Korir et al., 2023; Li et al., 2021; Slade & Prinsloo, 2013) Competence and interest of the involved (especially third) parties should be considered (Alzahrani et al., 2023). For example, if LA systems are provided by vendors outside of HE, they might not be fully aware of the specificities of the educational context or understand the pedagogical framework. They might also be more oriented towards profit than towards students' wellbeing and learning progress. Furthermore, the era of GenAI sheds a new, even more complex light on the ethics-related issues and opens new questions (Bond et al., 2024; Giannakos et al., 2024). For example, who should take responsibility if GenAI makes conclusions and decisions about humans?

Data Limitations Need to Be Considered. While on the one hand, it is ethically only acceptable to allow stakeholders (primarily students) the possibility to make an informed decision on their participation in LA, on the other hand, incomprehensive data can lead to biased results (Li et al., 2021). For example, some demographic groups or students with disabilities might be reluctant to consent to the use of their data, so data and analyses can therefore be biased. Moreover, there are different possible sources of data, and multimodal data (Mangaroska et al., 2020; Ochoa, 2022), like data collected via sensors and cameras, are not available in every educational context. These limitations should be taken into account at all times, and blind trust is not to be encouraged: learning data and LA results should always be considered critically and in context.

Algorithms Should Be Appropriate and Explainable. While LA normally uses machine learning and AI algorithms, statistical models and methods are not always used in an appropriate way. This can lead to results that make no sense in practice, resulting in untrustworthy LA. Therefore, great care should be taken of using models and methods that are fit for purpose (Albuquerque et al., 2024; Baker et al., 2023; Tao et al., 2024), minding the assumptions like homogeneity of variance or normal distribution. Moreover, LA should consider the differences in learning contexts, which calls for inclusion of contextual variables. Here, the question opens whether AI can account for the specifics of fields of study, courses, teaching and learning approaches, and the way they are used in a specific learning context. In this sense, it is important to distinguish between the predictive models relying on small (local) and big data. Furthermore, the intersection of LA and GenAI should be further explored, being mindful that, while machine learning includes known algorithms, how GenAI concludes is unknown. However, to enable trust in LA, we should aim for the explainability of algorithms and avoiding black boxes.

Transparency Should Be Upheld Throughout the Entire Process. It can be viewed as a multidimensional concept encompassing clarity, accuracy, and the disclosure of information within organizations. Clarity ensures that information is understandable and meaningful, accuracy guarantees it is perceived as precise, and information disclosure highlights the availability of valuable insights (Schnackenberg et al., 2021). Specifically, we should be mindful of ensuring transparent presentation of what data is being collected, for what purpose, how it is going to be analysed, and the results used. Moreover, when it comes to algorithms, maintaining transparency is valuable, but not always feasible with the GenAI.

4 DISCUSSION

We believe that the presented considerations play an important role in supporting not only a more widespread adoption of LA, but the adoption of LA that can be and is trusted by the stakeholders. It should be noted, though, that areas of responsibility differ among the stakeholders, and that not all of the considerations are equally important with respect to each group.

Responsibility and accountability have been identified in previous work (Svetec & Divjak, 2025) as a horizontal aspect of ensuring the trustworthiness of LA, including both its social and technological aspects. And while the said work, based on an analysis of previous research, focused primarily on institutional responsibility, here we would also like to consider the responsibilities of other stakeholders (Figure 2).

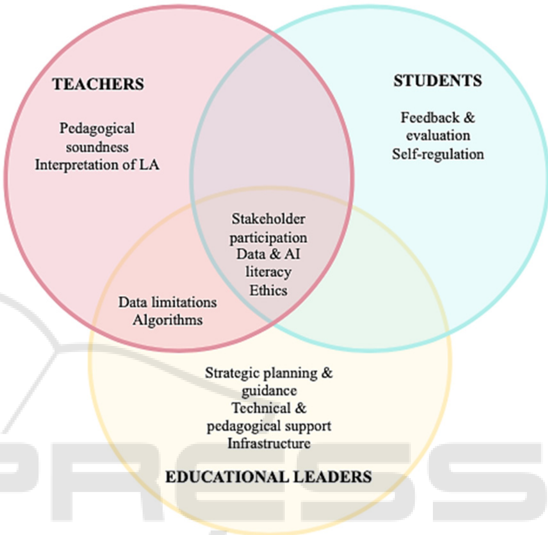

Figure 2: Venn diagram of stakeholder areas in ensuring trustworthy LA.

First, when it comes to the level of educational systems and institutions, the essential role is to be played by educational leaders, at different levels of decision-making. They are the ones who are, above all, responsible to implement strategic planning and provide guidance, which can make the implementation of LA meaningful, well-focused, transparent, and therefore more trustworthy. Strategic planning should include data collection and problem analysis, decision-making, followed by monitoring, evaluation and timely interventions if needed (agile approach) (Divjak & Begičević Ređep, 2015). On a more concrete level, educational leaders are those who should take care of strategic financial investment and ensure the prerequisites in terms of technical (e.g., infrastructure) and human resources (e.g., developers, third party providers). In some contexts, this can also include setting up specialized units providing LA on an institutional level (e.g., LA in national or institutional student information systems). Importantly, educational leaders should also ensure technical and pedagogical support for educators and students, whether in the form of technical assistance, teacher training or possibly AI assistance. When it comes to investment, this also includes monitoring and evaluation of tangible and intangible benefits and the return on investment.

Second, when it comes to "closing the loop" by introducing LA-based educational interventions in the classroom, the responsibility belongs to the educators, especially teachers. They are in charge of ensuring the pedagogical soundness of the teaching and learning process, including meaningful learning design. If this basis is not firmly established, and aligned with the principles of constructive alignment (Biggs, 1999), the soundness and explainability of LA can be questionable, and LA results can make little sense in terms of improving teaching and learning. Furthermore, educators have the essential role in interpreting the results of LA, using their pedagogical knowledge, considering their students' individual needs, and reacting in a way that can support the successful acquisition of learning outcomes.

At the intersection of the responsibilities of educational leaders and educators, there is the awareness of the data limitations and the possible bias stemming from incomprehensive data. Furthermore, these stakeholders should be mindful of the appropriate use of (explainable) algorithms and statistical models, as well as the risks of using GenAI. It is essential to note that lack of consideration for the data bias and inappropriate algorithms, including GenAI, possibly affecting the accuracy and fairness of LA, as well as insufficient consideration of the specific learning and cultural context, can present a risk of poorly targeted interventions that can even have a negative impact on learning.

Third, there are students, who should be in the center of all LA endeavors. Their area of responsibility is, on the one hand, related to the provision of information and feedback on what they consider important and useful in terms of LA (Divjak et al., 2023), as well as what kind of support they need (e.g., training, revision of curricula). For example, to ensure a student-centered approach, students should have the opportunities to pose questions they would like LA to answer and share their visions of LA assistance (Silvola et al., 2021). On the other hand, it is upon students to self-direct their learning based on the outputs of LA (Schumacher & Ifenthaler, 2018), with the support of interpretations provided by educators. For example, LA can provide personalized feedback related to specific tasks, and students are autonomous in deciding how to use it not only in that particular context, but also in their further learning practice and adaptation of their learning strategies.

Finally, all the three groups of stakeholders share the responsibility to ensure stakeholder participation, to enable the development of human-centered LA systems (Buckingham Shum et al., 2024). Furthermore, it is essential that they develop the levels of data literacy and AI literacy that is necessary for the implementation and understanding of LA. And last but not least, much has been discussed and researched on the topic of ethics in LA and AI, and while it is not specifically highlighted in this position paper, it should be clear at all times that working in line with ethical standards is the crucial prerequisite for ensuring trustworthy LA. This includes a number of aspects, from basic privacy and data security assumptions, to providing the stakeholders with the right information and the possibility to decide on how, why and by whom their data will be used.

When it comes to the stakeholders, discussing their responsibilities is only one side of the coin. On the other side, it is also important to look at which considerations they find important. This may be closely related to the question of cultural perspective, as an additional aspect to explore in order to design *culturally aware* and *value-sensitive* LA (Viberg et al., 2023).

5 LIMITATIONS AND FUTURE WORK

This paper has a more conceptual nature and tries to provide an overview of a complex topic, with the roles of stakeholders which are in essence intertwined. It builds on the previous literature review (Svetec & Divjak, 2025) by providing expert views which consider recent developments in the area of trustworthy LA, encompassing issues related to the rapid development and spreading of GenAI. Future work should provide a more practical perspective, looking into actual research case studies, to provide insights into practices, challenges, limitations and opportunities as perceived by stakeholders in particular instituions. Our assumption is that stakeholder perspectives might differ if we consider the specificities of HE contexts, pedagogical traditions, institutional visions and missions, governance models, as well as cultural factors.

6 CONCLUSION

Based on current research and discussion among international experts in learning analytics (LA), in this position paper, we outlined what we believe to be the fundamental considerations for the trustworthy implementation of LA. The said considerations pertain to strategic guidance and support, pedagogical soundness and human interaction, stakeholder engagement, data and AI literacy, ethics, data limitations and meaningful use of algorithms, as well as ensuring transparency of LA processes. We also discussed the responsibilities of stakeholders (primarily educational leaders, educators, and students) related to the said considerations. Finally, we opened some questions for further research and discussion, such as how culture affects trust and the perceived trustworthiness of LA.

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