Implementing Learning Analytic Systems in Educational Institutions: The Importance of Transparent Information for User Acceptance

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Abstract: Learning analytics (LA) systems have to meet high standards to ensure effective implementation in educational institutions, but knowledge about which factors play the most important role for users is limited. With two studies, we investigate the importance of different attributes of LA systems (Study 1) and the influence of different information fragments (i.e., benefits, drawbacks, and auditing information of the LA system) on users' (i.e., students and teachers) perceived fairness and attractiveness of the institution (Study 2). In Study 1, we conducted a choice-based conjoint analysis to examine the relative importance of fairness, accuracy, audits, and methods of use. Our results show that both students and teachers consider fairness to be the most important feature. In Study 2, we conducted an experimental video vignette study to examine how different fragments of information influence perceived fairness (i.e., informational justice) and attractiveness of the institution. We show that more information increases students' and teachers' acceptance, even when potential drawbacks are communicated, although the results of the teacher sample are less pronounced overall.

1 INTRODUCTION

In recent years, digitalization and the implementation of algorithm-based systems increased rapidly (Fischer et al., 2023; Mai et al., 2022). This development can also be observed in educational institutions (Winter et al., 2021). Schools and universities started to offer online learning, resulting in teachers having to assess student performance online. Learning analytics (LA) systems can improve this process and support teachers and students to make the learning process more effective (Martin and Ndoye, 2016). LA involves the process of measuring, collecting, analyzing and reporting data about learners and their environment (Siemens and Baker, 2012). The data is used to improve understanding of learning processes and to optimize both the learning experience itself and the learning environment in which it takes place (Ifenthaler and Drachsler, 2020). LA systems can measure learners' activity and consistency in using the learning platform, but also provide information on how well students complete their exercises and prepare for exams (Mai et al., 2022). Based on this, predictions are made and LA systems can help identify at-risk learners and support learning success (Siemens and Long, 2011).

Despite this, LA systems are not yet widespread, particularly in Germany, and the process of implementing a LA system is not well understood (Ifenthaler et al., 2021). Discussions often include concerns about the fairness and accuracy of the analysis (Roberts et al., 2016). Although algorithms and the use of artificial intelligence (AI) can increase the objectivity of decisions (Kaibel et al., 2019), biased training datasets can lead to unfair tendencies and systematically discriminate against certain groups (Köchling and Wehner, 2020; Greller and Drachsler, 2012).

Exploring factors that mitigate perceived uncertainties is crucial for safe implementation of these systems. Current literature highlights a gap in understanding the conditions under which users are

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receptive to learning platforms with integrated LA (Schumacher and Ifenthaler, 2018). Furthermore, little is known about how educational institutions can enhance users' perceptions of fairness in LA systems (Roberts et al., 2016).

Hence, first, it is important to know what LA systems should look like from the users' perspectives and to assess how to minimize users' concerns about fairness and accuracy, thereby giving credit to a user-centered design and making users feel more comfortable implementing LA systems in their educational routines (Lawson et al., 2016). Based on this knowledge, systems can be designed to be efficient and supportive. Yet the significance of different aspects of LA systems, including audits, has not been thoroughly studied (Schumacher and Ifenthaler, 2018). Therefore, we investigate the relative importance of auditing LA systems for users in comparison to other features, such as fairness, accuracy, and methods of use, with a choice-based conjoint analysis (Study 1).

Second, in Study 2, we conducted an experimental vignette study to examine the role of transparent communication of a newly introduced LA system for users' perceived fairness and organizational attractiveness. Transparent information is crucial for introducing new technologies to convey the context of their usage and functionality (Lawson et al., 2016). Following the reasoning of justice theory, the communication of information creates a sense of being actively involved in decisions (Colquitt, 2001). This can foster a more favorable assessment of emerging technologies, thereby promoting increased acceptance of LA systems within educational settings (Greenberg, 1994).

2 BACKGROUND AND THEORY

Educational learning platforms gather log data associated with learners' behaviors and actions (Almosallam and Ouertani, 2014), enabling automated analysis and enhancing information accessibility about learners (Mai et al., 2022). This information can be used to promote learner reflection or to predict learning success (Greller and Drachsler, 2012). LA facilitates information-based interventions for students, which enables adaptive and personalized learning. In this study, we only focus on algorithmic LA systems that can predict learners' success.

Although LA systems offer various benefits for enhancing learning processes, they come with challenges that might decrease users' perceptions of fairness and their acceptance of the system.

In education, data about learners is sensitive, which is the reason why the use of data is a critical issue (Khalil and Ebner, 2015). Furthermore, LA systems are trained by existing data. If this training data is biased LA systems replicate or even reinforce biases (Mehrabi et al., 2022), resulting in potential discrimination based on gender, origin, or religion (Köchling et al., 2021). Hence, it is crucial to avoid biases from a technical perspective, but users also need to have the feeling of a fairly treating system.

The acceptance of LA systems can also depend on the accuracy of the algorithm, as errors can also arise from inaccurate data used by algorithms and lead to errors in user evaluation (Mehrabi et al., 2022). These errors are often unnoticed and therefore cannot be reported (Kim, 2017).

Due to these concerns regarding the use of LA systems, it is useful to conduct an audit. Audits aid in early problem detection and bias prevention (Calders and Zliobaite, 2013; Riazy et al., 2020; Rzepka et al., 2022). A regular audit is also recommended in the European Artificial Intelligence Act (European Commission, 2021).

To measure the effects of addressing the concerns on the user perceptions, we followed the reasoning of justice theory and measured perceived fairness by using one dimension of justice (Starke et al., 2022). Justice refers to "perceptions of fairness in decision-making" (Colquitt and Rodell, 2011) and can be categorized into four dimensions (Colquitt, 2001). In our research, the dimension of informational justice was of particular interest, which describes the extent to which justification and truthfulness are provided during procedures (Colquitt and Rodell, 2011). We assume that communicating information about LA systems will make users feel more involved in decisions (Colquitt, 2001). In addition, research by Shapiro et al. (1994) found that detailed explanations are perceived as more satisfying. Accordingly, information about the LA system can lead to the development of trustworthiness (Colquitt and Rodell, 2011) and, hence, acceptance of the system. Further, Langer et al. (2018) found that reactions to technologies are positively influenced by more information.

Based on these assumptions, we propose that transparent communication of relevant information enhances the acceptance of LA systems. Furthermore, we assume that perceived fairness positively influences students' and teachers' reactions to LA systems and, in turn, increases institutional attractiveness.

In this study, institutional attractiveness reflects individuals' attitudes towards the educational institution (Chapman et al., 2005), which is a key precondition for intentions and behavior according to the theory of planned behavior (Ajzen, 1991). University students and teachers have freedom in selecting their educational institution and employer. If a university lacks characteristics and support deemed suitable by students and teachers, they may find this university less attractive and choose another university. Thus, attractiveness of an institution is crucial to remain a competitive university (Platz and Holtbrügge, 2016).

This leads to our two research questions concerning the implementation of a new LA system: First, which factors of LA systems do students and teachers rate to be important? Second, how do these information elements influence the perceived fairness and the institutional attractiveness of a university?

3 STUDY 1

3.1 Study Design and Sample

We conducted our Study 1 and 2 between autumn 2022 and spring 2023. In Study 1, we employed a choice-based conjoint analysis, a popular experimental research design for evaluating the importance of certain factors due to its similarity to real-life situations and ability to elicit spontaneous decision-making (Balderjahn et al., 2009; Karren and Barringer, 2002; Shepherd and Zacharakis, 1999). In our study, participants were asked to imagine their educational institution implementing a LA system. They chose between two systems in several rounds, selecting their preferred option. The systems differed in randomized attributes, visually represented with icons and pictures for clarity (see Table 1).

The first attribute *methods of use* varied across two levels, therefore differentiating between LA systems that give a grade recommendation and the ones that additionally forecast the learning success. The *type of audit* differed in the verification of the system within the educational institution, by third parties or no verification at all. *Fairness of the analysis* included an equal treatment of all learners regardless of origin, gender or religion or an accidental unequal treatment. The fourth attribute described the *accuracy of the analysis*, which varied between the correct evaluations of seven, eight or nine out of ten learners.

The specifications of attributes allow 36 (2 x 2 x 3 x 3) possible combinations of a LA system. As more than 20 rounds can overwhelm the participants, we used a fractional factorial design and applied twelve rounds in our survey (Balderjahn et al., 2009). We tested the number of rounds with the preliminary counting test in Sawtooth based on 300 versions.

For the recruitment of our sample, we employed a European ISO-certified online sampling provider (ISO 20252:2019). Our sample consisted of 440 participants from Germany, including 212 teachers (M_{age} = 44.82) and 228 students (M_{age} = 21.23). 70% of the sample were female. We made a distinction between teachers and students because teachers benefit from the results of the LA process and are expected to take action based on those results, while students provide the data that is analyzed (Greller and Drachsler, 2012). This highlights the need to understand the preferences of both groups.

3.2 Results

To analyze the results, we used the Sawtooth Software Lighthouse Studio 9.15.0 and evaluated our data using Hierarchical Bayes (HB) model and counting analysis. While the HB model shows the importance (I) of the attributes in a ranking, the counting analysis rates the levels within the attributes (Orme and Sawtooth Software, Inc., 2002).

All groups (i.e., students and teachers) rated fairness (I = 34.95[SD = 14.47]) as the most important attribute of a LA system. The type of audit (I = 28.87[SD = 11.61]) was ranked second, followed by accuracy of the analysis (I = 28.23[SD = 10.61]). The least important attribute was the method of use (I = 7.95[SD = 8.42]).

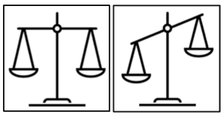
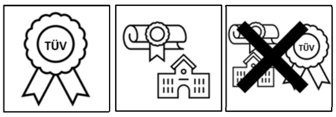
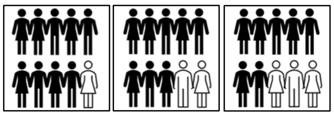
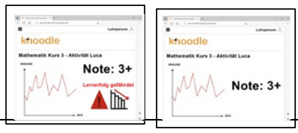
The counting analysis revealed the preferred levels of the different attributes. Table 1 shows the results of the level being selected of the times it occurred. All groups preferred a system with equal treatment of all learners regardless of origin, gender, or religion (0.70), audits verified by third parties (0.59), the correct evaluation of nine out of ten learners (0.62) as well as LA systems that provides grade recommendation as well as a prediction of the learning success (0.52).

4 STUDY 2

4.1 Study Design and Sample

While Study 1 highlighted the factors that are important for students and teachers when introducing a new LA system, Study 2 focuses on the extent to which communicating these information about LA systems may increase fairness perceptions and the institutional attractiveness of a university.

Table 1: Level rank of attributes.

Icons	Attributes and levels	*I*
	Fairness	
	The algorithm treats all learners equally (regardless of gender, origin, religion).	0.70
	The algorithm may inadvertently disadvantage learners (due to gender, origin, religion).	0.31
	Audit	
	A third party review of the system took place.	0.59
	There was a review of the system by the teaching institution.	0.56
	No review of the system took place.	0.35
	Accuracy	
	The algorithm correctly assesses 9 out of 10 learners.	0.62
	The algorithm correctly assesses 8 out of 10 learners.	0.50
	The algorithm correctly assesses 7 out of 10 learners.	0.38
	Methods of use	
	The algorithm gives a grade recommendation and additionally predicts learning success (successful completion of the course).	0.52
	The algorithm gives a grade recommendation.	0.48

We used a video vignette study, which is recommended to gain insights into the perceptions and attitudes of individuals (Shapiro et al., 1994). In these videos, the principal of a fictitious university, played by a trained actress, announced the implementation of a new LA system.

A total of eight vignette videos were included, resulting in a 2 x 2 x 2 factorial between-subject design to examine the effects of different combinations of information on users' perceptions of LA. Every participant watched only one of the eight videos. Each video aimed to manipulate the stimulus information in the following ways: (1) it highlighted the *benefits* of the LA system, including personalized feedback opportunities, (2) it discussed possible *drawbacks* of the LA system, such as the potential biases in algorithmic predictions, and (3) it provided supplementary details about an *external audit* of the LA system and explained that gender discrimination or ethnical discrimination against groups of people can be ruled out. Participants in one vignette (video 1: used as the reference category in the analysis) were solely informed about the implementation of a LA system, without any elaboration on its benefits, drawbacks, or the auditing process.

We assessed participants' perceived fairness using three items from the informational justice scale (Colquitt, 2001) (e.g., "Was the principal of the university open in her communication with you?"; Cronbach's alpha = .87). Participants' perception of the institutional attractiveness was measured with three items adapted from Aiman-Smith et al. (2001) (e.g., "The described university would be a good university to study at"; Cronbach's alpha = .94). Both scales were Likert scales (1 = strongly disagree; 7 = strongly agree).

The vignette study was conducted with two samples. We employed a European ISO-certified online sampling provider (ISO 20252:2019) to recruit students from German universities (n = 458; M_{age} = 30.33; female = 57%). The second sample included teachers from educational institutions in Germany (n = 269; M_{age} = 42.85; female = 58%), with participants recruited through social networks and the sampling provider.

4.2 Results

We analyzed the impact of the seven videos, each presenting various manipulation combinations, in contrast to the reference category (i.e., video 1 without further details on the LA system).

Detailed results are shown in Table 2. Although we found negative direct effects on institutional attractiveness, our results show that more information (i.e., benefits, drawbacks, audit) for students led to positive indirect effects on the institutional attractiveness. These relationships were mediated by perceived informational justice, which highlights the underlying mechanism governing users' responses to the provided information. Those vignettes containing information about the external audit of the LA system (i.e., Video 2, 4, 6, and 8) demonstrated the most substantial increase in informational justice

Table 2: Results of the student sample (Note. B = unstandardized effect; SE = standard error; b = standardized effect; N (students) = 458, N (teachers) = 269. Reference category: Information that LA is implemented without further details (video 1).

	Student Sample				Teacher Sample			
Direct Effects of the Video Vignettes	***B***	**SE**	***b***	***p***	***B***	**SE**	***b***	***p***
Video 2 Audit → Informational Justice	.64	(.21)	.20	.01	.42	(.30)	.12	.16
Video 3 Benefits → Informational Justice	.64	(.20)	.20	.01	.05	(.30)	.01	.88
Video 4 Benefits+Audit → Informational Justice	.76	(.21)	.24	.01	.10	(.30)	.03	.74
Video 5 Benefits+Drawbacks → Informational Justice	.66	(.21)	.21	.01	.08	(.29)	.02	.78
Video 6 Benefits+Drawbacks+Audit → Informational Justice	.78	(.21)	.24	.01	.82	(.31)	.22	.01
Video 7 Drawbacks → Informational Justice	.64	(.21)	.20	.01	.47	(.31)	.13	.13
Video 8 Drawbacks+Audit → Informational Justice	.64	(.21)	.20	.01	.16	(.29)	.05	.59
Video 2 Audit → Institutional Attractiveness	-.38	(.22)	-.09	.08	-.12	(.29)	-.03	.68
Video 3 Benefits → Institutional Attractiveness	-.42	(.22)	-.10	.05	-.17	(.29)	-.04	.55
Video 4 Benefits+Audit → Institutional Attractiveness	-.38	(.22)	-.09	.08	-.36	(.29)	-.08	.22
Video 5 Benefits+Drawbacks → Institutional Attractiveness	-.69	(.22)	-.16	.01	-.48	(.28)	-.12	.09
Video 6 Benefits+Drawbacks+Audit → Institutional Attractiveness	-.43	(.22)	-.10	.05	-.39	(.30)	-.09	.20
Video 7 Drawbacks → Institution Attractiveness	-.40	(.22)	-.09	.07	-.70	(.30)	-.15	.02
Video 8 Drawbacks+Audit → Institution Attractiveness	-.82	(.22)	-.19	.01	-.67	(.29)	-.16	.02
Effect of Mediator on Outcome Variable								
Informational Justice → Institution Attractiveness	.98	(.07)	.71	.01	.76	(.08)	.63	.01
Indirect Effects								
Video 2 Audit → Institution Attractiveness	.62	(.20)	.14	.02	.32	(.21)	.07	.10
Video 3 Benefits → Institution Attractiveness	.63	(.21)	.15	.01	.03	(.23)	.01	.88
Video 4 Benefits+Audit → Institution Attractiveness	.74	(.22)	.17	.01	.08	(.23)	.02	.74
Video 5 Benefits+Drawbacks → Institution Attractiveness	.65	(.22)	.15	.01	.06	(.22)	.01	.68
Video 6 Benefits+Drawbacks+Audit → Institution Attractiveness	.76	(.21)	.17	.01	.63	(.25)	.14	.02
Video 7 Drawbacks → Institution Attractiveness	.63	(.22)	.14	.01	.12	(.23)	.03	.56
Video 8 Drawbacks+Audit → Institution Attractiveness	.63	(.23)	.14	.01	.36	(.21)	.08	.06

perceptions, subsequently contributing to higher institutional attractiveness ratings.

To compare the two groups of teachers and students, we conducted a multi-group comparison in which we compared three models, an unconstrained model, a measurement invariance model, and a structural weights model (Steinmetz, 2013). The results show that the measurement invariance model ($\chi^2(10) = 82.069$, $p = .86$) does not differ significantly from the unconstrained model ($\chi^2(72) = 87.48$, $p = .20$), which in turn shows that both teachers and students understood the constructs in the same way. The structural weights model ($\chi^2(25) = 125.58$, $p = .01$), on the other hand, differs significantly from the measurement invariance model, which means that the model is different overall, that is, the groups differ significantly in their responses. This means that a group comparison makes sense

The results show differences in the effects between the two groups. For the direct effects on informational justice, the results of the students show clear positive directions, while only video 6 (i.e., the provision of information on all available information) led to an increase in the perception of fairness for teachers. In both groups, however, informational justice was positively related to institutional attractiveness. Concerning the direct effects of the videos on institutional attractiveness, we observed negative effects for the students, when potential drawbacks were mentioned (videos 7 and 8). With regard to indirect effects, the results show that video 6 with all information had a positive indirect effect on institutional attractiveness in both groups.

5 DISCUSSION

By conducting two empirical studies, we investigated the relevance of different characteristics of LA systems as well as the role of transparent information for fairness perceptions at educational institutions. The results show that especially the fairness aspect is a sensitive and relevant characteristic, and great importance should be attached to ensuring a fair evaluation by the systems. Furthermore, we found that transparent communication can increase fairness perceptions and thus also the perceived attractiveness of an institution.

In particular, the results of our conjoint analysis underline the fairness aspects and show the importance of external audits for both teachers and students. In contrast, the methods of use are not highly relevant, suggesting this does not need to be prioritized during system implementation. However, ensuring proper verification and technical bias prevention is still crucial.

The results of our vignette study shed light on the role of transparent information about the benefits and drawbacks of LA for students. We also show that information about an existing system audit by an external institution has an additional positive influence on perceptions. This shows that users perceive LA systems more positively the more information they receive—even if they are made aware of possible drawbacks. Although it may seem counterintuitive to point out drawbacks of the LA system, informing users of potential drawbacks is paramount, especially from an ethics perspective.

At the same time, our results show that students perceive a system to be fairer when they receive information that the LA system has been audited, which raises the need for universities to seek audits of their LA systems. Not only will this ensure that LA systems are functioning well from a technical and fairness perspective, but it will also help students assess whether they accept this new technology.

The results imply that teachers are apparently less easily influenced by the information provided to them, or that they themselves already have clearer opinions on the topic of LA. Another explanation may be that teachers see their profession as a job that they have to do anyway, even if new LA systems are introduced. Students, on the other hand, might change their educational institution if they do not like the LA system or if the provided information about the LA system is insufficient. In sum, our results suggest that it is important to provide students and teachers with all available information, as they are both affected by new LA systems.

Our findings have practical implications for higher education institutions, planning to implement LA and aiming to maximize users' acceptance. Given that literature is still in its infancy with regard to reactions to LA systems, our study adds to this literature by showing that revealing different information fragments to users has distinct implications for their perceptions and assessments of the institution. This has practical implications for the design and auditing of LA systems prior to their implementation and underscores the need to transparently communicate benefits, drawbacks, and the audit that has been performed by institutions.

In particular, both studies have highlighted the crucial role of audits, preferably by an external body, which in turn can ensure a fair assessment of students. The recommendation by the European Commission (2021) to audit systems based on artificial intelligence can therefore be supported and underlined as relevant by our findings.

6 LIMITATIONS

Our research is not without limitations. First, we conducted our studies with German-speaking participants. An exploration of our research questions in other countries with their own peculiarities (i.e., the state of digitization in educational instructions) would be an interesting and important avenue for future research.

Second, the novelty of LA systems presents a challenge for users, particularly concerning their usage scenarios. Despite employing visual aids in our studies to improve understanding, many users may lack prior experience with LA systems, hindering their full comprehension and empathetic engagement (Köchling and Wehner, 2020; Simbeck, 2023).

Third, in Study 1, to avoid overwhelming the participants (Balderjahn et al., 2009), we focused on just four attributes derived from existing literature and discussion surrounding LA. However, it is crucial to acknowledge the potential existence of other significant attributes and factors, which might emerge through additional research or during actual LA system implementation.

7 CONCLUSION

In order to ensure a meaningful use of LA systems in educational institutions, LA systems have to be accepted by all users. In Study 1, we investigated the importance of different attributes of a LA system and found that the fairness of the LA system and an external audit are most important for students and teachers. In Study 2, we investigated the influence of different information fragments on users' perceived fairness and institutional attractiveness of a university. Our results show that all users value more information about the LA system, even though possible drawbacks were communicated. However, the results for students and teachers differ significantly, indicating that students who are affected by the predictions of LA systems are more sensitive to the provided information in comparison to teachers. Future research is needed to investigate successful ways of implementing LA systems and to highlight the positive aspects for all user groups.

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