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Six Practical Recommendations Enabling Ethical Use of Predictive Learning Analytics in Distance Education

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Abstract
The progressive move of higher education institutions (HEIs) towards blended and online environments, accelerated by COVID-19, and their access to a greater variety of student data has heightened the need for ethical learning analytics (LA). This need is particularly salient in light of a lack of comprehensive, evidence-based guidelines on ethics that address gaps voiced in LA ethics research. Studies on the topic are predominantly conceptual, representing mainly institutional rather than stakeholder views, with some areas of ethics remaining underexplored. In this paper, we address this need by using a case of four years of interdisciplinary research in developing the award-winning Early Alerts Indicators (EAI) dashboard at a distance learning university. Through a lens focused on ethical considerations and informed by the practical approach to ethics, we conducted a case study review, using 10 relevant publications that report on the development and implementation of the tool. Our six practical recommendations on how to ethically engage with LA can inform an ethical development of LA that not only protects student privacy, but also ensures that LA tools are used in ways that effectively support student learning and development.

Notes for Practice

- LA has a number of ethical checklists and guidelines, developed mostly by experts in the field, rather than being based on empirical work.
- There is limited understanding of how proposed ethical rules are practised in daily LA decisions. Practical ethics and interdisciplinary research should guide the application of ethics in LA.
- Six practical recommendations are proposed for the ethical use of LA in HEIs:
  1. End users should be actively involved in the design and implementation of LA tools
  2. LA should be inclusive by considering diverse student needs
  3. HEIs should act upon LA data and communicate the added value of adopting LA tools
  4. Students should benefit from LA through a clear plan of support interventions
  5. HEIs should test LA data for hidden bias by engaging with diverse stakeholders
  6. Institutional LA ethics policy should be reviewed and updated regularly through practical ethics and interdisciplinary research

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Learning analytics, practical ethics, learning analytics dashboards, case study

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1. Introduction

Predictive learning analytics (PLA) dashboards utilize predictive analytics and artificial intelligence (AI) to forecast students' future learning behaviours and outcomes. Students can benefit from such insights by self-regulating their learning to improve their grades and motivation to study (Schumacher & Ifenthaler, 2018). Teachers can use PLA dashboards to enhance their professional development by proactively engaging with their students and providing timely support that can help improve student outcomes (Herodotou et al., 2021). Overall, these processes can help higher education institutions (HEIs) advance their institutional reputation by bringing more individuals to learning and/or professional success (Berendt et al., 2020).

Despite the exciting potential of PLA, and more generally learning analytics (LA) tools, they are often discussed through a lens of possible harm and harm avoidance (Kitto & Knight, 2019). For example, there are concerns that algorithms may contribute to the "status quo" in education by amplifying existing gender and ethnicity biases, or that LA tools might eventually grow into aggressive tracking of individuals. These concerns make it clear that care is required to ensure that LA techniques are implemented ethically in ways that maintain human agency and, indeed, improve educational systems (Berendt et al., 2020). Many of these ethical concerns reflect past alarming precedents, such as a recent educational scandal in the UK when, during COVID-19, thousands of school pupils were downgraded by an algorithm that changed grades based on a school's previous performance and other factors (Porter, 2020). Another example is the recent debate about the uptake of online exam proctoring technologies, which, as many believe, are rooted in problematic assumptions about educational fairness and authoritarian pedagogical approaches (Lee & Fanguy, 2022).

The need to design and implement algorithmic tools responsibly has been recognized in the field of AI, where we see the ongoing attempts to develop ethical frameworks and novel approaches to understanding ethics (Bilal et al., 2020; Floridi et al., 2018; Neubert & Montañez, 2020). In the field of LA, however, research suggests that ethics is not yet firmly established or adhered to (Ferguson et al., 2016). Discussions about ethics in LA have been predominantly theoretical; therefore, there is a salient need for practical ethics guidelines informed by LA practitioners' direct experiences of virtuous decision-making (Cerratto Pargman & McGrath, 2021; Tzimas & Demetriadis, 2021). Ideally, such guidelines should not only focus on harm avoidance, but provide actionable directives that pave the way to the responsible realization of the exciting potential LA tools have to offer. The few studies that do propose evidence-based ethics guidelines are mostly exploratory and/or relatively small scale, often examining early adoption of LA tools through, for example, single case studies (Viberg et al., 2018).

Given these insights, this paper adopts a case study approach (Yin, 2013) and reports on a four-year practical application of LA at a distance learning institution — The Open University (OU) UK. This choice of university was deemed appropriate for our case study for several reasons. First, its Early Alerts Indicators (EAI) dashboard is one of the few large-scale implementations of PLA in the field (Herodotou et al., 2020b). It is now available across all university faculties for its 170,000+ undergraduate students. Second, it has been extensively researched in terms of its impact and use by involving stakeholders (teachers, students, educational managers). Third, it has gained international and university-wide recognition by winning the second prize in the UNESCO ICT in Education competition in 2021 (https://bit.ly/3s82ijw), a DATA IQ award in 2020 (https://bit.ly/3o9w1Yw), and two university awards for research and teaching impact.

In this paper, we reviewed all work about the EAI implementation at the OU published when we wrote this case study (N = 10 studies) in relation to ethical considerations. We first identified ethical dimensions featured in the 10 reviewed studies and formulated five practical recommendations for the ethical implementation of LA based on the issues raised. We then compared and contrasted these with existing conceptual frameworks on ethics (Drachsler & Greller, 2016; Sclater, 2016; Slade & Prinsloo, 2013), and with the current ethics policy at the OU (Open University, 2014). This prompted us to formulate a sixth recommendation that concerned a need to establish and/or update an institution-wide ethics policy that would complement existing ethical processes.

Our proposed practical recommendations are mainly targeted at HEIs that wish to implement LA. However other stakeholders, such as PLA dashboard designers and researchers, and those working in the AI regulation field may also find these recommendations useful.

2. Practical Ethics as a Way Forward

Most work on ethics in LA has been conceptual, proposed by experts, and completed independently of concrete empirical cases (Cerratto Pargman & McGrath, 2021; Tzimas & Demetriadis, 2021). Such work has not always been used well by practitioners (Kitto & Knight, 2019), and there is little understanding of how ethical rules are practised in daily LA decisions. In particular, Cerratto Pargman and McGrath (2021) showed that the least addressed ethical area so far is enabling positive interventions, pointing to specific circumstances in which institutions should intervene due to analytics, so that a student could benefit from additional support. An earlier literature review of Viberg et al. (2018) also found that despite the identified potential of LA for improving learner experience, there has been little transfer of the suggested potential into HE practice over the years, and only 18% of the reviewed studies in Viberg et al. (2018) even mention "ethics." The review of Cerratto Pargman and McGrath (2021) further showed that even though some ethical dimensions of LA are unpacked more than others, the majority (67%) of the reviewed studies refer to LA systems in generic terms. As ethical concerns may vary according to the type of LA tools considered (e.g., PLA dashboards), it becomes challenging to gauge the ethical issues specific to certain LA tools.

Furthermore, most studies on LA ethics represent institutional (50%) rather than student views (36%) on the topic (Cerratto Pargman & McGrath, 2021). Very few PLA dashboards, for example, are informed by direct and comprehensive student and teacher evaluation, even though these tools are developed for use by students and teachers (Rets et al., 2021). A systematic literature review on dashboards by Bodily and Verbert (2017) showed that out of 94 articles identified on student-facing dashboards, only 6% included some form of student needs assessment. As Broughan and Prinsloo (2020) further stated: "In the social imaginary of LA, students are habitually seen as the producers of data and as data-objects, but not as equals" (p. 619). These insights raise the need to engage with ethical issues from a messy ground-up perspective, which would complement the substantial conceptual work conducted on ethics in LA (Drachsler & Greller, 2016; Sclater, 2016; Slade & Prinsloo, 2013). The studies that have started to address the issue of involving the end users in the evaluation and design of LA, are mainly positioned within human-centred LA (Buckingham Shum et al., 2019), rather than within an ethics implementation perspective. For example, Dollinger et al. (2019) conducted a case study of how designers co-created LA platforms with teachers that have now been used by over 30,000 students. They also provided recommendations for how to best carry out such participatory design of LA tools.

Besides the aforementioned gaps in LA ethics research, the extent to which the latest concerns and developments in LA ethics are reflected in institutional and/or other widely adopted ethics frameworks is unclear. For example, Tsai and Gašević (2017) compared eight existing policies for LA and found that communications between relevant stakeholders in the reviewed policies are top-down, limited to the aspects of what, how, and why data are collected; none of the policies mentioned a review and evaluation of the impact of LA on learning. The authors concluded that a solid process of evaluation would allow institutions to build successful cases to promote LA not only internally, but also in the wider HE sector.

An approach to ethics that can help critically reflect on LA impact is practical ethics. It aims to bridge theory and practice and study how principles of moral behaviour apply to real-world scenarios (Ellis, 2020; Kitto & Knight, 2019). It is increasingly proposed as a framework for the ethical design of AI tools (e.g., Bilal et al., 2020; Neubert & Montañez, 2020). For example, Floridi et al. (2018), who formulated 20 recommendations for implementing "Good AI Society" using practical ethics, discussed the ethical principles, borrowed from bioethics, that undergirded their practical recommendations:

1. Beneficence — AI should benefit and empower as many people as possible
2. Non-maleficence — AI must not cause any harm either from the intent of humans or from unpredicted behaviour of the tool (e.g., unintentional nudging of human behaviour in undesirable ways)
3. Autonomy — AI must not impair [the] freedom of human beings to set their own standards and norms and be able to live according to them
4. Justice — AI should promote justice and seek to eliminate all types of discrimination (warns against the risk of bias in data sets used to train AI systems)
5. Explicability — AI users should understand and hold to account the decision-making processes of AI (asks questions, *"How does it work?"* and *"Who is responsible for the way it works?"*)

However, very few studies have discussed these principles in the context of developing and using AI in education. Practical ethics are starting to be considered in LA (e.g., Kitto & Knight, 2019; Tzimas & Demetriadis, 2021), but as yet have only gained limited attention. Emerging claims are being made that this ethics approach can provide a constant and encompassing reference against which the decision-making stakeholders in LA can critique the learning infrastructure that they (and others) are creating (Kitto & Knight, 2019).

An important question raised in some ethics studies is whether "ethics quality" is measurable and the extent to which one can formally assess ethics practices. For example, some machine ethics researchers argue that the plurality of values that motivate people and ethical decision-making requiring an estimation of the wider implications of one's actions make it difficult to translate these values into a consistent computational specification (e.g., Brundage, 2014). Crigger and Wynia (2013) discussed the tools used to evaluate ethics quality in bioethics, such as a survey on staff perceptions about ethical practices in their organization. The authors concluded that while one cannot put a number on ethics quality, ethics evaluation may be possible by examining processes rather than outcomes, staff experiences rather than feelings, and involving the widest range of stakeholders, instead of "only staff who are identified with an organizational ethics committee or consultation service" (Crigger & Wynia, 2013, p. 4).

The highlighted value of practical ethics in LA, the shortage of empirical evidence-based LA ethics guidelines (Cerratto Pargman & McGrath, 2021; Tzimas & Demetriadis, 2021), as well as the recommendation that researchers in the field should participate in building the ethics guidance that helps the field grow in a safe and credible manner (Kitto & Knight, 2019; Lang et al., 2018) inspired this study.

3. Case Study of the Early Alert Indicators (EAI) Dashboard

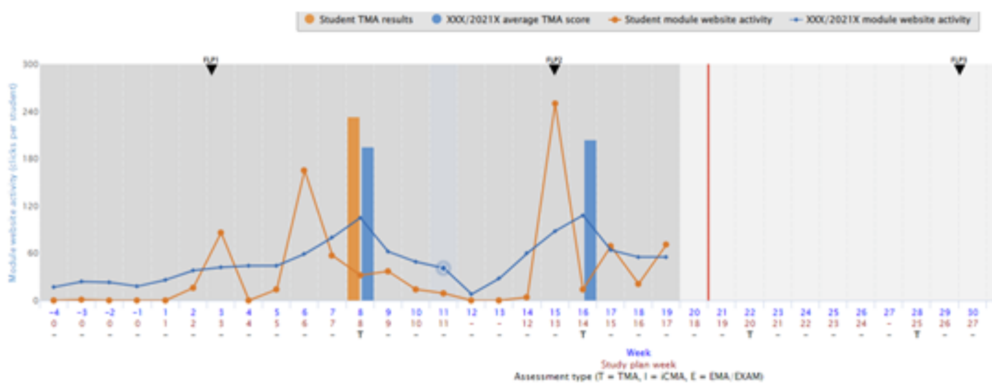
This case study review was guided by the following research questions:

- *What ethical dimensions are featured in the 10 studies reviewed as part of this case study?*
- *What practical recommendations for the ethical implementation of LA can be formulated based on this review?*
- *How do these recommendations compare and contrast with existing frameworks on ethics, and with the current ethics policy at the OU?*

3.1. Description of the EAI Dashboard

EAI is a teacher-facing predictive learning analytics (PLA) tool, developed and released at the OU. It forecasts students at risk of failing their studies based on both short- and long-term predictions. Short-term predictions indicate whether an individual student is going to submit their next teacher-marked assignment (TMA) for a specific course. These predictions are calculated based on three types of information: 1) static data known about a student before the start of a course, such as their highest previous education; 2) assessment data, such as previous scores, extensions of assignments, and attendance at tutorials; and 3) data from student interactions with the virtual learning environment (VLE) generated daily. A gradient boosting machine (GBM) algorithm, which learns from errors made when creating previous GBM models, is trained to generate these predictions. Short-term predictions are available to teachers on a weekly basis.

Long-term predictions refer to the probability of whether a student will reach specific course milestones, including completing and passing a course and returning for studies in the next academic year. These predictions are based on models generated through logistic regression analysis of a set of 70 explanatory variables; they are generated at the start of a course and updated periodically at four points throughout the course duration.



Milestone	Prediction to complete	Prediction to pass
At start (02/10/21)	71 - 80%	71 - 80%
FLP1 (14/10/21)	81 - 90%	71 - 80%
FLP2 (31/12/21)	91 - 100%	81 - 90%
FLP3 (31/03/22)	NA	NA

Assignment	Risk of NS	Grade prediction	Actual	Extension	Prediction based on
TMA 01	Submit	Pass 3	78	yes	• summary activity in week 7 • homepage activity in week 8 • summary activity in week 8 • homepage activity in week 6 • 60 previous credits failed • homepage activity in week 7
TMA 02	Submit	Pass 2	NS	—	• TMA01 • oucontent activity in week 14 • TMA01 has been submitted. • occupation • oucontent activity before last TMA • 60 previous credits failed

Figure 1. Anonymized student data in the EAI dashboard

Note: **"VLE engagement graph":** an interactive graph indicating an individual student's engagement (brown) measured against the average student in the cohort (blue). Columns indicate prior TMA scores. Lines indicate weekly VLE activity, measured as a number of mouse clicks made during each week of the course. **"Long-term predictions":** these predictions are recorded as a percentage of likelihood of a student completing and passing the course. They are generated at the start of a course and updated at four points throughout the course. **"TMA predictions and scores"** provides predictions of future TMA non-submissions (NS), the potential banded grades (e.g., Pass 3 — grade C, TMA scores between 55 and 69) and scores, and information on whether the student has been granted an extension. Each prediction is accompanied by a list of the most significant attributes that contributed towards the generated prediction (e.g., low previous score or low activity in the weeks before the assignment cut-off date).

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Short- and long-term predictions are communicated in the EAI dashboard through several visualizations: 1) a graph indicating the overall cohort's engagement with VLE in the current and previous course presentation, as well as a student's individual performance and assessment outcomes compared to the average of the cohort (see Figure 1); 2) a colour-coded system indicating in green students who are likely to pass their next TMA with a grade of 55% or above, in amber — those with a probability of passing their next TMA with a grade of 40–54%, in red — students at risk of non-submission or fail (below 40%) (see Figure 2); and 3) long-term predictions (see Figure 2).

Teachers are advised to check the dashboard every week and contact students flagged as red or amber to identify whether they need additional support.

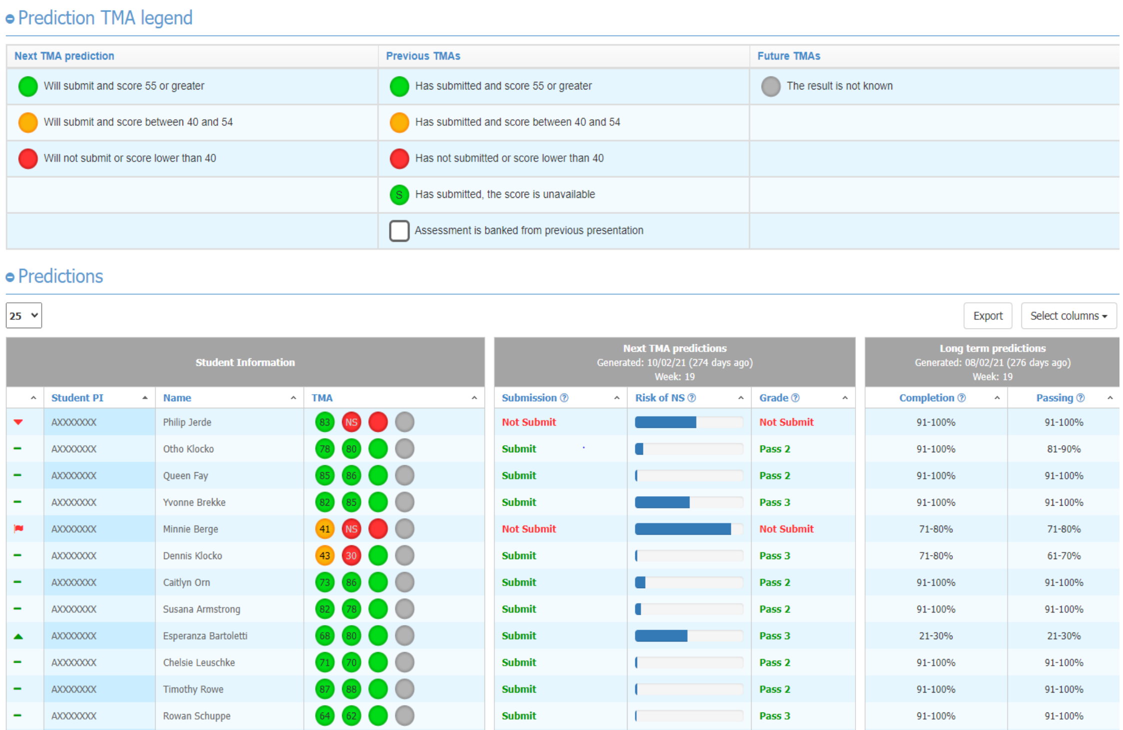

Figure 2. Teacher's view of the overall short- and long-term predictions of a given cohort in the anonymized EAI dashboard (all student names are pseudonyms)

Note: **Student information:** the list of students in each cohort and their awarded and/or predicted TMA scores (the colour use is explained in the legend above). Next TMA predictions: indicates the likelihood of each student in the cohort submitting their next TMA (green = Submit, red = Not Submit). The blue bar indicates the percentage risk of non-submission (the longer the bar, the higher the risk). Grade prediction indicates the potential banded grade each student is likely to receive (e.g., Pass 3 — grade C, TMA scores between 55 and 69). Long-term predictions: a percentage of likelihood of course completion by each student, as per the last recorded long-term prediction update.

3.2. Process of Analyzing EAI-Related Studies

The EAI dashboard has been evaluated at the OU through a four-year university-funded implementation (2017–2021) that aimed to identify whether the use of the tool can contribute to student completion and retention.

For the purposes of this case study review, we identified and reviewed all studies (N = 10) about the EAI implementation at the university, published when we wrote this manuscript. Eight of the studies were educator-facing. Besides examining the perceptions of teachers, they also engaged with other professional staff: instructional designers and curriculum managers (n = 3), the Student Support Teams (SSTs) (n = 1), senior HE managers (n = 1), as well as with the interdisciplinary LA project management team (n = 1) at the heart of the dashboard design. The other two studies were student-facing.

We didn't go beyond the identified studies, because 1) this case study aimed to engage with a specific LA tool, and 2) this is a single case study. As this case study reanalyzed published work about the case that did not necessarily explicitly discuss ethics, it is important to note our own situatedness (Haraway, 1988). At the point of conceptualizing this review, the first author was involved in a large-scale project looking into the ethics of design and use of AI algorithms in tech companies and had led one of the reviewed studies (Study 10 in Table 1). The second author led the OU's grant for EAI implementation and had been actively involved in conducting all reviewed studies. The third author was also part of the university's EAI implementation and led the work with the early adopters of the dashboard among teachers.

We followed a four-pronged approach to analysis in this case study review. First, we examined all studies in detail and identified any ethical issues either implicitly or explicitly raised in the studies. In our identification of the ethical issues, we were guided by the five ethical principles (e.g., beneficence, explicability) discussed in an earlier practical AI ethics study of Floridi et al. (2018). Second, we noted any practical recommendations that emerged from each elicited ethical consideration. For example, the ethical consideration raised in Study 1 was the lack of skills among educational stakeholders needed to use and act on PLA, which might ultimately deprive students of the support they could receive if their teachers were not able to use the tool. The two practical recommendations that follow from this issue and were discussed in the study were 1) the importance of dialogue and participatory methodology, which allowed this issue to surface, and 2) the institution's responsibility to support professional development of staff. The third step involved inductive thematic analysis (Boyatzis, 1998) using each practical recommendation as a unit of analysis (see Figure 3). This allowed us to collate our analysis into five practical recommendations that can inform engagement with ethics in LA.

Finally, we benchmarked our recommendations, using the compare and contrast qualitative analysis approach (Ryan & Bernard, 2003, p. 91), against three existing ethics frameworks (Drachsler & Greller, 2016; Sclater, 2016; Slade & Prinsloo, 2013). These frameworks were chosen in light of them being well cited, discussed in the recent systematic LA ethics reviews (Cerratto Pargman & McGrath, 2021; Tzimas & Demetriadis, 2021), and covering a broad range of LA processes, rather than focusing on single aspects, such as privacy or LA design. We also included the OU's ethics policy in this comparison (Open University, 2014) to examine how real-life LA implication maps against the university's own guidelines. This analysis prompted us to formulate a sixth recommendation that concerned the need to establish and/or update an institution-wide ethics policy that would complement existing ethical processes.

Table 1 summarizes each reviewed study and notes the ethical considerations and practical recommendations that emerge. We used a colour-coding system to map each practical recommendation onto the ethical principles that guided our analysis in the first step and to match them with the themes in Figures 3 and 4. The choice of colours was arbitrary with the intent to make them friendly for readers with common types of colour blindness.

Table 1. Case Study Review: Ten EAI Dashboard Studies

Studies reviewed	Summary of each study	Ethical dimensions discussed	Practical recommendations
		Educator-facing studies	
Study 1: Rienties et al. (2018)	Workshop with 95 participants (teachers, instructional designers, curriculum managers) examining their perceptions of LA visualisations, using the Technology Acceptance Model. **Methods**: Surveys, observation notes, post-workshop briefings. **Findings:** Most participants were positive about the perceived usefulness of the dashboard, and negative about its perceived ease of use. Those with higher technology acceptance scores were more positive about the LA workshop.	- Reference to the University's ethics policy, no other direct reference to ethics; - Most participants indicated that they would need additional training and follow-up support to be able to use the tool.	- Participatory design of LA tools by collecting feedback from teachers. - Institution's responsibility to support professional development of staff and train teachers on digital skills and the use of the tool.
Study 2: Herodotou et al. (2019a)	A mixed-methods study about the effectiveness of 59 teachers using PLA to support 1325 students. **Methods:** Log files of teachers' engagement with the dashboard; semi-structured interviews. **Findings**: The more teachers make use of PLA, and the more successful students were in previous courses, the likelihood of students completing and passing a course increases. Teachers' positive perceptions about the usefulness of the tool vs. their actual infrequent use of it.	- Reference to the University's ethics policy, no other explicit reference to ethics; - Most teachers used EAI infrequently, primarily for a short period of time just before the submission of an assignment; - Some teachers accessed only specific features of the tool and avoided others.	- Since teachers' usage of PLA was found to relate to student performance – social responsibility of teachers not accessing the tool systematically and not intervening with students flagged as at risk. - Social responsibility of teachers to also support high-performing learners. - Institution's responsibility to trial and propose best ways of supporting students at risk. - Institution's responsibility to improve the learning design of courses as informed by analytics. - Institutional responsibility to motivate teachers to use EAI.

Study 3: Herodotou et al. (2019b)	This study compared the use of PLA to other methods and their impact on student performance. **Methods:** Teachers were clustered into 'high', 'average', and 'low' groups by their use of the dashboard, their students' overall course performance was compared. The performance of students in the cohorts of 'average' and 'high' groups was further compared to the cohorts in the previous two years of the same teachers when they didn't have access to EAI. **Findings**: Student's performance was significantly greater in the 'high' group than in the other groups. Better student outcomes were recorded the year teachers accessed PLA than the year they did not.	- No explicit reference to ethics; - Teachers with high PLA usage had more students passing their courses compared to teachers who did not use or made very limited use of it; - Improved student learning outcomes can be achieved when teachers engage with PLA throughout the course, as opposed to only the first few weeks.	- Evidence of the positive benefits from accessing student data. - Social responsibility of teachers who are not using PLA to support students. - Institutional responsibility to motivate teachers to use EAI.
Study 4: Herodotou et al. (2020a)	This study compared the OU's method of selecting students at risk to using EAI. The study further compared two intervention methods: contact before the start of the course and after enrolment (control group) vs. an additional text message and a phone call/email (intervention group). **Methods**: Randomised control trial **Findings**: EAI was shown to correctly identify a greater percentage of students at risk. Strong statistically significant differences were observed for the intervention group, suggesting that an additional contact helped at-risk students remain engaged.	- No explicit reference to ethics; - Value of interpersonal contact for students' sense of belonging; - Value of including factors, such as the Index of Multiple Deprivation (IMD) in PLA and analysis; - EAI can be used to also identify students with high probabilities of success; - Unclear which intervention method was more effective - phone call or email. If some students chose to remain passive – did they not want to be contacted by their teacher and receive an intervention?	- Institutional responsibility to find effective ways of selecting students at risk and supporting them. - Institutional responsibility to maximise success of all students, and not only at-risk students. - Responsibility of dashboard designers to trial diverse factors that best contribute to the tool's prediction accuracy in a fair way. - Institutional responsibility to ensure interdisciplinary collaboration around LA. - Institutional responsibility to allow students to retain the power to decide if they want to receive the intervention. - Institutional responsibility to explain to students how and why their LA data are used, and – using evidence base – what the benefits of teacher interventions are for learning.
Study 5: Herodotou et al. (2020b)	This study looked at EAI adoption in terms of numbers of teachers and other staff accessing the dashboard. These findings were discussed with (a) an interdisciplinary LA project management team, and (b) teachers in an evaluation workshop. **Methods**: Log files of EAI usage; participatory stakeholder workshops. **Findings:** The number of teachers accessing EAI increased considerably since the start of the LA implementation project. Critical factors to LA adoption were faculty's engagement with LA, teachers as "champions", evidence generation and dissemination, teachers' digital literacy, and their conceptions of teaching online.	- Reference to the University's ethics policy, no other explicit reference to ethics; - Interdisciplinary work in LA is more likely to lead to a more comprehensive EAI design, which in turn will enable EAI adoption and use; - Participatory research – engaging teachers as co-researchers from the start of the project can help overcome barriers to EAI adoption; - Variation of strategies and persistence of their use to act on EAI data among teachers implies that EAI use might not be equally effective for all students.	- Teachers should be involved in the design, testing and dissemination of analytics. - Importance of using PLA in online settings, where other clues about student performance are not present. - Value of including diverse voices in the process of design through interdisciplinary research.
Study 6: Rienties et al. (2020)	This study reported on insights from a workshop with 42 participants (senior HE managers, teachers, and professional support staff) about their experiences with LA and its desired future affordances. **Methods**: Participatory stakeholder workshop **Findings**: The study identified four areas where more work should be done: Communication, Personalisation, Integrated design, and Evidence-based LA tools that communicate feedback to staff.	- Reference to the University's ethics policy; - Linking learning design data with assessment, tuition, and behaviour data can help personalise teaching and learning; - LA can support student needs considering disabilities and well-being, which can help maximise study time; - Limiting access to the dashboard only to teachers deprives students of a detailed personal insight into their learning behaviour; - Lack of supportive culture around LA at the university under study.	- Institutional responsibility to use LA to improve the design of courses. - Institutional responsibility to support specific student needs and help with study success. - Institutional responsibility to allow students make use of their LA data and strengthen their right to make decisions about their learning. - Institutional responsibility to create a supportive culture around LA that would enable teachers to make greater use of the dashboard and act on the EAI data where needed.

Study 7: Herodotou et al. (2021)	This study examined the effectiveness of sending email reminders to teachers, nudging them to check EAI. **Methods:** Log files from a 37-week online course and 11 in-depth interviews with teachers. **Findings**: The degree of usage varied among teachers and, overall, tailed off as the course progressed. All participants reported that they had read the email reminders, yet their response to them varied from prompting further action and checking the dashboard to taking no action.	- Reference to the University's ethics policy, no other direct reference to ethics; - Negative implications for students, whose teachers displayed low engagement with EAI; - Different teacher perceptions about their role in supporting students; - Despite lack of anxiety reported in using IEA, issues of limited data literacy among teachers were raised.	- Social responsibility for teachers to check on and act to support students. - Institution's responsibility to ensure teachers act upon student data and find ways to promote its use to the teaching community. Also, communicate the ethical implications of NOT doing so. - What is the ethical responsibility of online teachers? Proactive vs. reactive support. - Institutional responsibility to understand teachers' current feedback practices, which, in turn, will help design and promote LA interventions. - Institutional responsibility to train teachers on digital skills and the use of EAI. - Institutional responsibility to ensure participatory design of LA research.
Study 8: Hlosta et al. (2021)	This study examined the impact of using PLA on students to identify how to minimise the awarding gap. **Methods**: Nineteen teachers used EAI to obtain predictions of which students were at risk of failing and got in touch with them to support them (intervention group). The learning outcomes of these students were compared with students whose teachers did not use the tool (control group). **Findings:** The results demonstrated a positive impact of acting on EAI on students' performance, particularly those from low socio-economic backgrounds, as measured by the Index of Multiple Deprivation (IMD).	- No reference to ethics; - EAI that accounts for wider factors, such as IMD, can help to better determine what groups of students are most in need of interventions and are most likely to benefit from LA systems.	- Use of student data to benefit students with low performance. - Social responsibility of teachers to access PLA data and act upon it. - Social justice and equity when teachers are accessing analytics for students that are likely to struggle. - Institutional responsibility to ensure that EAI designers rigorously test their models for bias and explore the added value of the factors they use in predictions.
Student-facing studies			
Study 9: Herodotou et al. (2020c)	This study collected the perspectives of 19 students about PLA. **Methods**: Online forum activity **Findings**: Students supported the idea of the university providing their teachers with access to performance and engagement data and acting upon it. Comparisons to other students were not seen as a useful feature of the dashboard, yet study recommendations were perceived useful.	- No ethical issues raised by students; - PLA tools that do not capture core aspects of the learning experiences, such as amount of time spent studying offline, previous subject knowledge, work or family issues, tutor contact may create a wrong picture of student progress and disinform a student.	- Participatory design of student-facing dashboards to identify their needs by involving students. - Ethical implications of showing comparative data to students – promoting a competitive narrative? - Institutional responsibility to trial the factors in EAI design that contribute to the most accurate representation of student learning.
Study 10: Rets et al. (2021)	This study examined perspectives of 21 undergraduate students about a student-facing EAI dashboard. **Methods**: In-depth interviews with EAI data displaying participant's individual predictions and learner data used as a stimulus for the discussions. **Findings**: Students favoured study recommendations but not peer comparisons, unless supported by qualitative insights. Different needs reported due to age, self-efficacy, and high performance.	- Reference to the University's ethics policy; - Students did not raise any concerns over control of data by the university – university as gatekeeper of data for supporting learning; - EAI can be used not only to help at-risk students, but also to support high-performing students; - Some students were sensitive towards off-track predictions, the situations when the predicted grade about their past assessment was lower than the actual grade. This has implications for student trust and correctly informing the student about their learning.	- Participatory design of student-facing dashboards considering diverse needs that tailor solutions to different sub-cohorts. - Promote trust and transparency of data by detailing how these are calculated and used. - Predictions should not be based on student demographics but engagement and performance data to prevent reproduction of societal stereotypes.

Note: The colour coding was introduced to the third column of Table 1 to match its content with the themes in Figures 3 and 4. The educator-facing and student-facing studies appear in the table in the chronological order of publication.

3.3. Ethical Dimensions of the Reviewed EAI-Related Studies

The biggest ethical consideration raised in the reviewed studies concerned the finding that there is a positive relation between teacher engagement with the PLA data and student learning outcomes and the evidence that despite perceived usefulness of the EAI tool, most teachers used it infrequently and unsystematically (Studies 2–5, 7, 8). This ethical consideration is rooted in the ***beneficence*** ethical principle (Floridi et al., 2018) — education is a common good, and AI should benefit and empower as many people as possible. A sizable body of LA research also refers to the ***"duty to act"*** ethical principle (e.g. Prinsloo & Slade, 2017; Sclater, 2016; Slade & Prinsloo, 2013) — a primary responsibility of educators and educational institutions to make use of any available resources that can help their students learn successfully. While some research literature challenges the idea that LA can help institutions improve student support (e.g., Ferguson, 2019), the evidence in our reviewed studies further endorses the "duty to act" ethical principle. Furthermore, while students at risk of drop out and students from disadvantaged backgrounds were shown to benefit the most from PLA interventions (Studies 4 and 8), our reviewed studies raised the ethical consideration of also supporting high-performing students (Studies 2, 4, 10). For example, Study 10 showed that EAI has great potential to maximize the learning of "distinction" students by indicating how their results were directly impacted by interacting with different kinds of learning materials, or provide insights into the elements of effective learning — not only on the course for which they saw their data in the EAI, but also in terms of their long-term development as learners.

At the same time, Study 4 reflected on the fact that after its randomized control trial, which examined the effectiveness of additionally contacting the students identified by EAI as at-risk on their course completion rates, it was still unclear as to which intervention method was more effective, and why some students chose to remain unresponsive. This ethical consideration concerning student agency to participate in the PLA interventions corresponds to the ***autonomy*** ethics principle — AI must not impair [the] freedom of human beings to set their own standards and norms and be able to live according to them; and humans should always retain the power to decide which decisions to take.

Another ethical consideration concerned the finding that teachers do not adopt the EAI tool by osmosis, and there are specific factors that either facilitate (e.g., recognition of the added value of using the tool) or inhibit (e.g., lack of understanding of the tool's features) their willingness to use it (Studies 1, 5, 6, 7). For example, in Study 1, 86% of teachers indicated a need for additional training and follow-up support for working with EAI. This consideration corresponds to the explicability ethical principle (Floridi et al., 2018) — AI users should be able to understand and hold to account the decision-making processes of AI.

We also elicited a number of ethical considerations that concerned the design of EAI in the reviewed studies. Studies 4 and 8 raised the need to investigate factors to include in predictions that can help minimize bias and identify the groups of students most in need of support. For example, the use of the Index of Multiple Deprivation (IMD; Ministry of Housing, Communities & Local Government, 2019) as a proxy of socioeconomic background in PLA and regression analysis in Study 8 facilitated the evidence that students coming from deprived neighbourhoods are most likely to benefit from PLA interventions. This consideration corresponds to the justice ethical principles (Floridi et al., 2018) — AI should promote justice and seek to eliminate all types of discrimination.

Although the reviewed student-facing studies (Studies 9 and 10) showed that students did not raise any concerns over how or why the university uses their data, these studies warned about the risk of off-track predictions or EAI failing to capture aspects of the learning experience, such as offline study time or previous subject knowledge. These risks may lead to low predictive accuracy of the tool or to providing disinformation to students about their learning. These ethical considerations tap into the non-maleficence ethical principle (Floridi et al., 2018) — AI must not nudge human behaviour in undesirable ways.

Figure 3 gives a snapshot of the thematic analysis conducted with the practical recommendations (N = 39) that emerged from each ethical consideration raised in the reviewed studies. For reasons of limited space, we only include three recommendations per theme, using similar colour coding to that of column three in Table 1 and to Figure 4. While we indicate the most immediate corresponding ethical consideration for each theme on the left side of the figure, they form an interconnected system of ethical behaviours. For example, for EAI to be actively used to support student success and well-being (beneficence), teachers need to understand how the tool works, and the good and harm it can cause (explicability). Teacher and student feedback on the design of the tool can prevent potential harms arising from its use (non-maleficence), but it can also make the tool more robust (justice) and promote its adoption (beneficence).

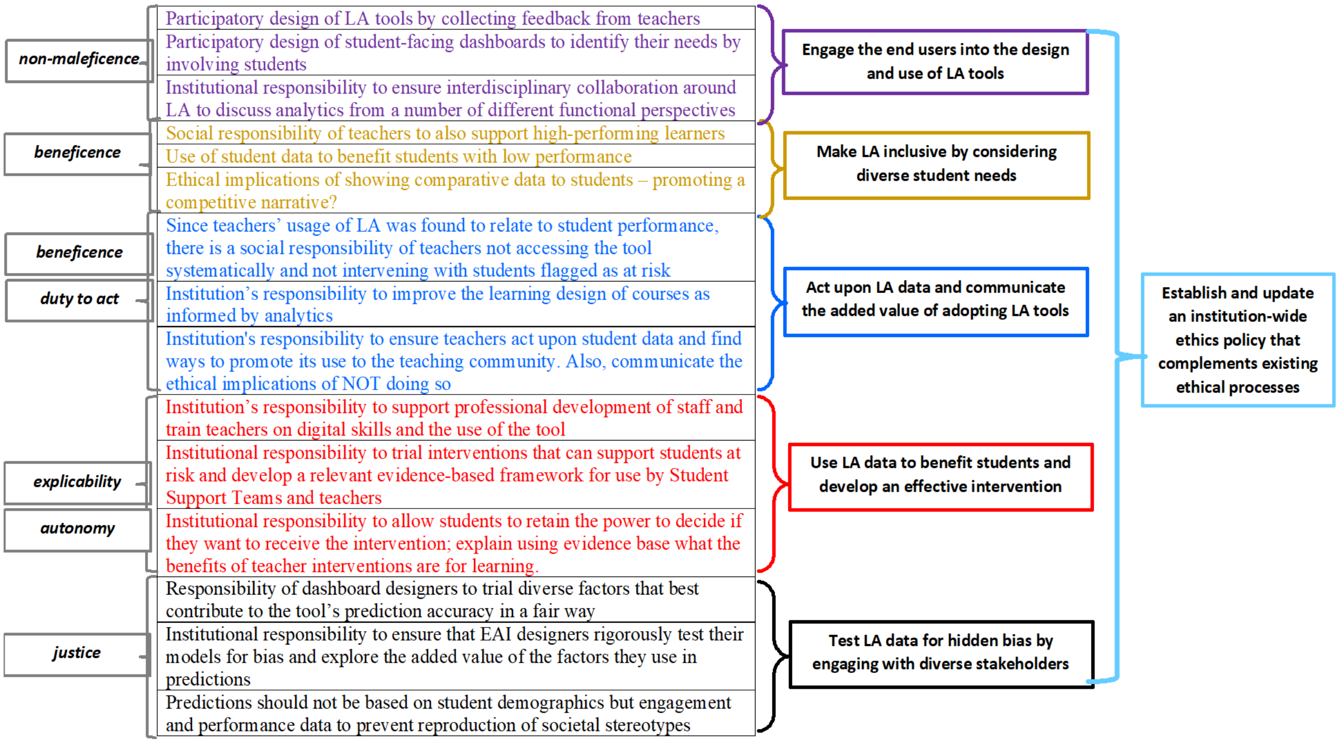

Figure 3. Thematic analysis of the practical recommendations that emerged in the reviewed studies

4. Practical Recommendations for the Design and Implementation of Ethical LA

This section will discuss the themes elicited in our analysis of the practical recommendations that can inform ethical implementation of LA.

4.1. Six Practical Recommendations

Five of the six overarching practical recommendations elicited in this study are discussed below and visualized in Figure 4, at the end of section 4. The sixth recommendation is discussed in section 4.2, after Tables 2–5.

Recommendation 1: Engage the end users in the design and use of LA tools

A key theme that became evident in the 10 reviewed studies is the need to actively involve the end users — teachers and students — in the design and implementation of LA tools. For example, Study 1 (Table 1) collected data from 95 teachers when the EAI dashboard was still in the beta stage of development at the OU. The study showed that teachers were able to provide constructive feedback on how to visualize LA data. Among the suggestions made was that comparative data would provide students with the necessary contextualization of a course. Study 5 further showed that a bottom-up approach to LA, a close consultation with teachers, understanding why some teachers are more proactive in adopting the tool than others, can substantially facilitate a scalable implementation of LA within the institution. In follow-up studies, Studies 9 and 10 identified what elements of the EAI tool were perceived as useful by students. Students noted that comparative data might evoke different responses by different students, and that study recommendations were welcomed by all students.

Another recommendation that emerged from our case study review is the need to do LA research interdependently as part of interdisciplinary research teams. Not only do such research teams have access to more cross-faculty resources (e.g., access to log files to analyze the level of adoption of LA tools), but their reflection on LA tools is informed by both Machine Learning and educational theories. There are emerging research alerts in the wider literature about the difficulties that arise when producing knowledge on AI independently, particularly without involving social scientists. For example, by mathematically defining social concepts such as ethics and fairness, AI systems may fail to recognize their full meaning, which can be at times procedural, contextual, and contestable (Neubert & Montañez, 2020; van den Broek et al., 2021).

Including teachers and students as part of the research and design team in LA and ensuring that what is designed responds to the teaching and learning context addresses an important gap in LA ethics, where most studies have focused on institutional, rather than the end user views (Bodily & Verbert, 2017; Cerratto Pargman & McGrath, 2021). More LA studies that use participatory research design (e.g., Buckingham Shum et al., 2019; Dollinger et al., 2019) and are conducted by interdisciplinary teams can help collect examples of how ethical considerations play out in LA practice. This, in turn, can support the development of practical ethics in the field.

Recommendation 2: Make LA inclusive by considering diverse student needs

The initial intention for designing the EAI at the OU was to support students flagged as at risk of failing their studies in order to increase their chances of passing. However, teachers noted other potential benefits of the EAI dashboard, in particular using predictive data to maximize the learning experience of well-performing students (e.g., Study 2). This could be achieved by providing students with additional study material and/or suggestions of how to improve their study approaches. Teacher communication with well-performing students could acknowledge and praise study efforts and identify study requirements specific to an individual student's needs.

Diverse student requirements were further noted in Study 10. Students expressed different preferences about potential features of a student-facing EAI. While all participating students perceived it as useful to have access to the study recommender (which proposed material to study for passing the next assignment), high-performing and mature students requested more recommendations about how to make their learning more effective. Also, the majority of participating mature students noted that the dashboard should have the functionality to point students to additional information or clarification. These should be written in an accessible, non-technical format, stating how the different elements in the dashboard are designed, why some predictions can be off track, and why mouse clicks can be considered a good indication of student engagement and, thus, learning. Such clarifications have the potential to increase the trustworthiness, and thus the perceived usefulness of the tool. Another implication from Study 10 was that the institution might consider collecting additional data about students in close consultation with them (e.g., information about their offline learning, their personal learning goals, as well as psychometric data, such as their levels of self-efficacy and anxiety) to make LA tools more personalized to them, as well as for the purposes of a more accurate representation of their learning.

These insights suggest that the process of designing an LA tool should be inclusive and consider the requirements of diverse end users. Moving away from a "harm-avoidance" approach, access to LA should be seen as a personalized approach to supporting specific student needs and — not only "saving" at risk students, but maximizing the learning experience of all students, including high-performing and older students.

Recommendation 3: Act upon LA data and communicate the added value of adopting LA tools

LA ethics should not only be concerned with the protection of student privacy and the ethical use of their data; it should also focus on how to allocate resources for effective and appropriate interventions within the institution to increase effective learning and teaching. This is particularly important considering previous research suggesting that most LA studies do not scale and do not lead to LA tools being taken up and widely used (Viberg et al., 2018).

Since the LA data are collected and analyzed by the university, it becomes unethical not to act upon it, particularly having research findings at hand that show the students flagged by EAI as being at risk of failing who are contacted by their teachers have higher chances of passing the course than students whose teachers are not using EAI (e.g., Studies 2, 3, and 8). It is the institution's responsibility to find ways to promote the use of LA tools to the teaching community, communicate their unique benefits, and provide teachers with hands-on training that draws on case studies of how teachers can interact with the LA data. For example, Study 5 showed that having teacher "champions" provide authentic, practice-based examples about how to use and act upon EAI insights, alongside regular dissemination of the peer-reviewed research findings about the effectiveness of the tool, facilitated its adoption at the OU. Regular interactive training workshops or a course aimed at further enhancing teachers' digital skills, as well as a faculty-wide policy detailing teachers' obligations in contacting and monitoring students can also be beneficial. Teacher support interventions should result from research showing LA's effectiveness with specific student groups and for specific learning goals. Studies that showcase the value of using LA to support marginalized students (e.g., Study 8) should form part of any LA initiative since they can guide decisions on how to support diverse groups of students.

Recommendation 4: Use LA data to benefit students and develop an effective intervention infrastructure

Another emerging overarching recommendation concerned how to support students at risk of non-submission or of failing their course. HEIs have an ethical responsibility to identify appropriate interventions to support students and to act on information identified by LA. For example, Study 4 showed that an additional contact made to students by the university's Student Support Teams (SSTs) early in the course, asking students about 1) how they feel about starting their course, 2) whether they have any concerns, and 3) whether they know where to look for help, were found to support student retention. Study 10 further showed that in some situations the knowledge that teachers were aware of the problem reduced student anxiety and acted as a motivation to engage with their studies more fully.

It is important to recognize that some students might not choose to use specific approaches such as phone contact. Therefore, a "one size fits all" approach may not be the best way forward. A proactive strategy that takes account of individual differences would give teachers and other stakeholders a basis upon which to plan to act. Regarding students, there should be clear communication as to how any data used may, or may not, have an impact on their assessment, performance, and communication with the university.

This practical recommendation corroborates the evidence from the recent systematic reviews on LA ethics, which call for more research studies to investigate ways for HEIs to act on the available LA data and establish effective interventions (Cerratto Pargman & McGrath, 2021; Prinsloo & Slade, 2017; Tzimas & Demetriadis, 2021). Enabling interventions was shown to be the least addressed research area, due to the pre-eminence of the harm avoidance narrative in LA ethics research and its dominant focus on the issues of privacy, transparency, and informed consent (Kitto & Knight, 2019).

Recommendation 5: Test LA data for hidden bias by engaging with diverse stakeholders

The quality of student information used as part of LA data, collected by an institution, should be reviewed and assessed, not only by software designers but also by social and learning scientists, to identify and mitigate potential implicit biases. For example, ethnicity was used in early algorithmic models in EAI at the OU as one of the variables identifying students at risk. Consultation with social scientists resulted in removing this data from the models given that the physical characteristics of individual students do not relate to their performance. In contrast, poverty and socioeconomic status indices would be better predictors of learning outcomes since they can affect educational opportunities and contribute to inequalities. Presently, the prediction models at the OU use the Index of Multiple Deprivation (IMD). IMD is a socioeconomic UK government initiative addressing relative deprivation in UK neighbourhoods. The data measures the percentage of people from each ethnic group who live in the most deprived 10% of neighbourhoods in the country based on seven indicators: income, employment, education, health, housing, environment, and crime levels (Ministry of Housing, Communities & Local Government, 2019).

This concern is in line with the wider AI literature, which calls for additional testing to be performed to ensure that any assessment behaviours that correlate with the individual's protected attributes, such as ethnicity, are either adjusted in the algorithm (de-weighted) or permanently removed from prediction models (e.g., Hassani, 2021) to ensure that predictions do not cause bias — i.e., individuals from one or more protected groups (e.g., ethnic minority students) are not predicted to perform at significantly different rates to the majority.

Given that this is a relative measure, further research on its use in prediction models is required. Is using IMD as a proxy for students at risk likely to overrepresent specific student groups unfairly? If this information is being used, should students be informed of its inclusion, and should teachers be guided as to how to interpret the meaning behind it? How does this measure perform in intersectionality conditions — e.g., gendered performance differences in science courses between students with and without low socioeconomic status? Furthermore, as this is a UK initiative, it does not collect the same information for overseas students.

Overall, there is an overarching complexity in using data to identify risk factors, raising the need for regular institutional ethics policy reviews. Having an open, ongoing discussion about this complexity among diverse stakeholders within an HEI can help establish a cohesive system of using LA for creating ethical and accurate representations of students.

4.2. Novelty of these Practical Recommendations

This section will look at the extent to which the ethical behaviours identified in this case study review match those addressed in the widely adopted frameworks for ethics in LA. In Tables 2–5 we compare and contrast the recommendations elicited in this case study review with three widely adopted frameworks for ethics in LA (Drachsler & Greller, 2016; Sclater, 2016; Slade & Prinsloo, 2013), as well as with the current ethics policy at the OU (Open University, 2014). This policy laid the groundwork for the adoption of LA at the OU in 2014 and for the implementation of the studies that formed the basis of this case review.

Slade and Prinsloo (2013) do not specify the methodology they used to develop an ethical framework for LA. Their six ethical principles point to the need for LA to be a transparent moral practice (LA practice should result in understanding of learning rather than measuring learning), and for students to be viewed as co-contributors, who voluntarily collaborate in providing data and access to data to inform LA. The framework also raises considerations linked to the storage and permanency of LA data, analyzes vulnerability due to misinterpretation, and examines the implications of an educational institution ignoring LA data.

Using the methods of literature review and an advisory board consultation, Sclater (2016) formulated eight ethical principles for an LA code of practice. Similarly to Slade and Prinsloo (2013), Sclater (2016) also pointed to the need for LA to benefit students and to be carried out transparently, as well as warning against the risk of LA reinforcing discriminatory attitudes or presenting invalid data. Sclater (2016) further focuses on the data-related issues around informed consent, the agency of students to opt out of data collection, data protection, and anonymization.

Drachsler and Greller (2016) followed similar methods to those of Sclater (2016) — a literature review and several workshops with experts — to devise their LA ethics checklist. In contrast to Slade and Prinsloo's (2013) and Sclater's (2016) frameworks, Drachsler and Greller's (2016) ethical principles are formulated more as practical action points that should be considered by managers and decision makers planning LA implementation. Similarly to Sclater (2016), the framework raises ethical considerations linked to privacy, data anonymization, informed consent, and transparency. Along similar lines with Slade and Prinsloo (2013), Drachsler and Greller (2016) mention the need to involve all stakeholders and data subjects in LA implementation for transparency purposes, provide data subjects with access to the data collected about them, and train staff.

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In contrast to Slade and Prinsloo (2013) and Sclater (2016), Drachsler and Greller (2016) do not focus on the "duty to act" on ethical principles or LA interventions.

Finally, the current ethics policy at the OU, released in October 2014, features eight ethical principles. The policy addresses privacy issues while also recognizing the importance of transparency regarding the different types of information used. It also specifies that it is the remit of the university to reassure students that any information used for LA was already provided during their studies (for example, demographic information provided on enrollment), through the process of informed consent. The policy further details that the data analyzed for LA purposes are intended to support students in their studies and are not used for any purpose beyond this.

Our comparison of the four frameworks discussed above with the recommendations elicited in this case study review (Tables 2–5) showed that these four ethics frameworks have been developed mostly by experts in the field. In contrast to our recommendations, they were not informed by practical ethics or any specific longitudinal practical implementation of LA within a HEI. Furthermore, these frameworks refer to LA systems in generic terms, while our recommendations focus on PLA and the adoption of the EAI dashboard.

Table 2. Contrasting Our Recommendations with Slade and Prinsloo (2013)

Framework	Key points of the framework	Compare and contrast points with our practical recommendations
Slade and Prinsloo (2013)	(1) LA as moral practice; (2) LA should engage students as collaborators; (3) Student identity and performance are temporal dynamic constructs; (4) LA should acknowledge that student success is complex and multidimensional; (5) Higher Education should be transparent regarding the purposes for which LA data will be used and under which conditions; (6) Higher Education cannot afford not to use data.	**Similar points between our recommendations and the framework:** - Both recognise that LA is grounded in power relations between learners and HEI; both see students as active agents in LA. - Both recognise that interventions need to be effective and morally necessary; LA data should not be ignored. - Both recognise that despite the potential of LA to gain a comprehensive understanding of student learning, LA data are incomplete and vulnerable to misinterpretation. **Contrast points:** - Slade and Prinsloo's framework is grounded more in the "harm avoidance" narrative and is more concerned with privacy, transparency, storage, and permanency of LA data. In contrast, our recommendations are grounded in practical ethics. - Our recommendations cover a wider range of end users (e.g., teachers), and introduce the importance of interdisciplinarity in LA. - Our recommendations provide more targeted pointers as to how interventions can be carried out effectively, stress the importance of communicating the value of LA; discuss the need to train teachers on the use of LA tools. - Our recommendations provide more insights as to how LA can be inclusive and raise awareness about the need to reflect on the kind of demographic factors used in LA data analysis.

As can be further seen in Tables 2–5, both the four ethical frameworks and our recommendations raise awareness about the asymmetrical power relations in LA between the student and the HEI, touching upon the need for LA to benefit students (Slade & Prinsloo, 2013; Sclater, 2016; Open University, 2014). However, the main focus of the four ethical frameworks with which we compared our recommendations is on the issues of privacy, transparency, and data ownership. In contrast, our recommendations centre around effective, ethical interventions and inclusive LA, providing practical pointers as to how these can be achieved.

Table 3. Contrasting Our Recommendations with Sclater (2016)

Framework	Key points of the framework	Compare and contrast points with our practical recommendations
Sclater's (2016) code of practice (JISC)	(1) Responsibility; (2) Transparency and Consent; (3) Privacy; (4) Validity; (5) Access; (6) Enabling positive interventions; (7) Minimizing adverse impacts; (8) Stewardship of data.	**Similar points:** - Both recognise that there are ethical and legal objections to LA, which have become impediments to the development and rollout of LA, thus potentially denying students the full benefits of predictive analytics and adaptive learning. - Both recognise that the key stakeholders who should benefit from LA are students; students' needs are at the heart of both frameworks. - Both touch upon the validity of LA data (e.g., our recommendations - off-track predictions; mouse clicks vs. student engagement) and that LA data should be seen in the wider context of an individual's experience. **Contrast points:** - Our recommendations focus on the insights of longitudinal practical implementation of ethical LA by an institution; Sclater's (2016) code is more abstract and conceptual - its key focus is on the need to decide who has overall responsibility for the use of LA at the institution, as well as on the issues of transparency, privacy, and consent. - Our recommendations cover a wider range of end users (e.g., teachers), and introduce the importance of interdisciplinarity in LA. - Our recommendations go beyond discussing the "obligation to act" and point to how effective and ethical interventions can be carried out in LA. - Our recommendations go beyond discussing the need for an institution to be careful not to prejudice students by categorising them and stress the need to reflect on the kind of demographic factors used in LA data analysis.

Table 4. Contrasting Our Recommendations with Drachsler and Greller (2016)

Framework	Key points of the framework	Compare and contrast points with our practical recommendations
DELICATE checklist (Drachsler & Greller, 2016)	(1) Determine: why do you want to apply LA? (2) Explain: what data will be collected for which purpose? (3) Legitimate: why are you allowed to have the data? (4) Involve all stakeholders and the data subjects; (5) Consent: make a contract with the data subjects; (6) Anonymise: make the individual not retrievable; (7) Technical: procedures to guarantee privacy; (8) External: if you work with external providers, make sure they follow national and organisational rules.	**Similar points:** - Both recognise that LA should be used purposefully, in a safe manner; - Both recognise the asymmetrical power relationship LA entails between the data controller and the data participant. - Both recognise the need to train staff to use LA for the benefit of students. **Contrast points:** - DELICATE checklist mainly focuses on privacy and "harm avoidance", while our recommendations are grounded in practical ethics. - DELICATE checklist does not specify who the data participants are, it is implied that they are students; our recommendations stress the importance of consulting with a wider range of end users (e.g., teachers) including students, and introduce the importance of interdisciplinarity in LA research and implementation. - DELICATE checklist does not focus on interventions and procedures for how interventions can be carried out ethically, in contrast to our recommendations. - DELICATE checklist does not focus on biases that can emerge during LA data labelling and analysis and/or when generating predictions. Our recommendations warn about the need to reflect on the kind of demographic factors used in LA data analysis.

Moreover, while the other frameworks also discuss the need to actively involve students in LA (Slade & Prinsloo, 2013; Drachsler & Greller, 2016; Open University, 2014), our recommendations stress the need to involve students not only for transparency purposes, but also to engage them in the design of LA tools. Our recommendations include a wider range of stakeholders (e.g., teachers) to discuss their role in ethical LA and suggest that HEIs need to partner with teachers to take full advantage of PLA tools. Our recommendations also further introduce the need for interdisciplinarity when researching and implementing LA, and stress the importance of promoting and communicating the unique benefits of PLA to the end users for its successful adoption. In contrast to Slade and Prinsloo (2013), Sclater (2016), and Open University (2014), our recommendations discuss the need to train teachers to facilitate the adoption of LA tools.

Finally, only two of the ethical frameworks (Sclater, 2016; Open University, 2014) have separate principles regarding the need to minimize adverse impacts on students by not prejudging or categorizing them. The unique contribution of our recommendations is that they stress the need for an interdisciplinary expert reflection on the kind of demographic factors used in LA data analysis, suggesting ways to test for bias.

Table 5. Contrasting Our Recommendations with the Ethics Policy at The Open University (2014)

Framework	Key points of the framework	Compare and contrast points with our practical recommendations
Current ethics policy at the OU (Open University, 2014)	The OU in the UK was the first HEI to develop, approve and implement a policy on the ethical use of student data for LA (The Open University UK, 2014). Its key principles are as follows: (1) LA is an ethical practice that should align with core organisational principles, such as open entry to undergraduate level study; (2) The OU has a responsibility to all stakeholders to use and extract meaning from student data for the benefit of students where feasible; (3) Students should not be wholly defined by their visible data or our interpretation of that data; (4) The purpose and the boundaries regarding the use of LA should be well defined and visible; (5) The OU is transparent regarding data collection and will provide students with the opportunity to update their own data and consent agreements at regular intervals; (6) Students should be engaged as active agents in the implementation of LA (e.g., informed consent, personalised learning paths, interventions); (7) Modelling and interventions based on analysis of data should be sound and free from bias; (8) Adoption of LA within the OU requires broad acceptance of the values and benefits; (organisational culture) and the development of appropriate skills across the organisation.	**Similar points:** - Both recognise that students are active agents in LA; - Both recognise the importance of acting on LA data through interventions; - Both emphasise that LA should be used for the benefit of the students. **Contrast points:** - OU ethics policy reflects early days of LA adoption and recognition. It focuses on “harm avoidance” in LA, privacy and transparency; - Our recommendations cover a wider range of end users (e.g., teachers), and introduce the importance of interdisciplinarity in LA; - Our recommendations put more attention to how effective interventions can be achieved with LA and stress the importance of communicating the value of LA and training teachers; - Our recommendations stress the need to analyse and address diverse student requirements with LA and account more for the different sources of bias in LA, as well as raise awareness about the need to reflect on the kind of demographic factors used in LA data analysis.

These comparisons of our practical recommendations with the four LA ethics frameworks show that the ethical behaviours elicited in this case study and those discussed in the alternative frameworks do not fully match. This is particularly concerning, as the OU’s ethics policy has been designed to guide LA implementation. Our analysis supports the earlier research of Tsai and Gašević (2017), who found that existing ethics policies might be missing important aspects of real-life applications, such as the need to evaluate interventions or facilitate communication between a wide range of stakeholders. Our findings on this mismatch prompted us to formulate a sixth recommendation on the ethical implementation of LA.

Recommendation 6: Establish and update an institution-wide ethics policy that complements existing ethical processes

Devising an ethics policy as to how student data should be used across an institution should be the starting point of using LA to support teaching and learning. Such a policy should be the result of open consultation with involved stakeholders, including students and teachers, and it should be updated periodically to reflect any changes in the fields of AI, LA, and teaching. Students new to an institution should be given time to engage with the policy and respond to it, ensuring that consenting to it is a conscious decision and not merely the ticking of a box during study registration.

As shown in Figure 4, an ethics policy should build upon existing practical ethics insights, and be implemented in an interdisciplinary manner. It should be reviewed and updated regularly (recommendation 6), give clear guidelines about how to engage end users with LA tools (recommendation 1), support the needs of diverse students including high-performing ones (recommendation 2), reinforce the social responsibility of acting on the data (recommendation 3), benefit students through a clear plan of support interventions (recommendation 4), and critically engage with the inclusion of specific data sets in predicting student outcomes (recommendation 5).

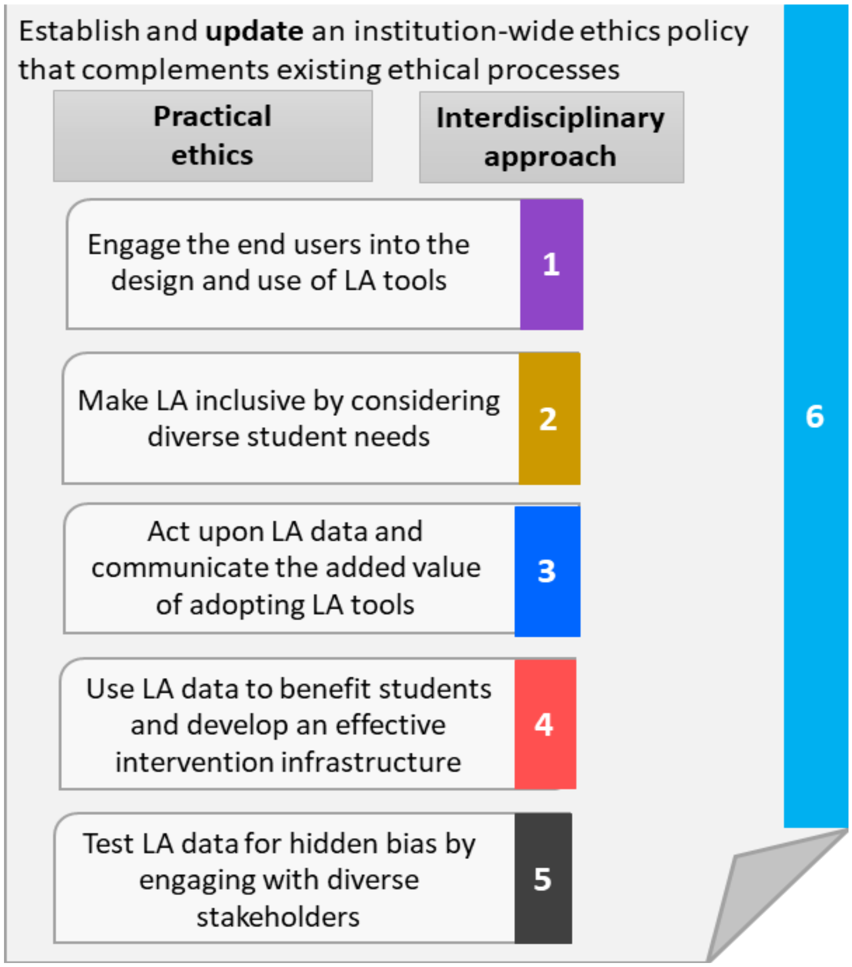

Figure 4. Visualization of the six practical recommendations for ethical LA elicited in this study

5. Conclusion

In this case study, we reviewed 10 publications that report on the four-year university-wide initiative of designing and implementing an LA tool — the Early Alert Indicators dashboard at The Open University. The review, undertaken through an ethics lens, allowed us to formulate six recommendations on how to engage ethically with LA in practice.

One limitation of this study is that it focused on a single LA implementation — one LA system in one HEI — suggesting that the proposed guidelines, while applicable to distance education, may come with shortfalls when applied to, for example, campus-based HEIs or LA tools with different features and functionality. A future direction for this work could be to use multiple cases and/or employ ethnographic methods of data collection and analysis, such as interviewing the project team on how their ethical questions and considerations evolved over time. This evolution has taken place; for example, the findings from Studies 1 and 2 on limited LA literacy skills among teachers led to the project team working closely with a group of teacher "champions" in Study 5 and beyond to provide training to an increasing number of teachers across the university. An ethnographic case study would help build a grounded theory of ethical LA implementation; distinguish between the ethical issues relevant to the different phases of design, deployment, and evaluation of the LA tool; examine the contradictions and links between ethical issues (e.g., privacy versus efficiency in PLA design); and weight the urgency of these differences.

Furthermore, we see our proposed six recommendations as bringing together key issues related to ethics and the design/implementation of LA systems in HEI. They can also be a starting point for future research that can apply, revise, and improve the proposed guidelines. Some of the proposed recommendations — such as the obligation to act and participatory design — have been discussed in existing ethics and human-centred LA work (Broughan & Prinsloo, 2020; Buckingham Shum et al., 2019; Prinsloo & Slade, 2017) but have not been brought together in a comprehensive way through an evidence-based lens, as this paper proposes.

As Viberg et al. (2018) mentioned, it was worrying that more than 80% of the LA papers they reviewed did not mention ethics at all. A similar issue concerned the 10 studies we reviewed in our case — only six of them referenced the university's ethics policy, and none explicitly engaged with ethics. We see the key contribution of our study as giving an example of how ethics can be "plugged in," critically reflected upon, and approached in a more systematic way in LA research. We also call for more LA studies to include a dedicated ethics section reflecting on emerging issues and underlying principles.

Benchmarking our recommendations against widely used conceptual LA ethics frameworks (Drachsler & Greller, 2016; Sclater, 2016; Slade & Prinsloo, 2013), and against the OU's existing ethics policy (Open University, 2014) revealed a key emphasis on issues of transparency, privacy, and informed consent. This focus corresponds to the dominant LA ethics narrative of "harm avoidance" — how the potential for student harm can be minimized (Cerratto Pargman & McGrath, 2021; Kitto & Knight, 2019). The studies reviewed in this paper and other recent LA ethics reviews (Cerratto Pargman & McGrath, 2021; Tzimas & Demetriadis, 2021) unearthed new, urgent, pertinent issues, such as involving diverse stakeholders in the conversation about LA ethics, finding new ways for LA tools to be used, designing features to provide insights into effective learning, rather than a fail or pass, as well as using the latest evidence-based methods to test for and mitigate bias.

No set of guidelines can keep up with the fast-evolving field of AI (van den Broek et al., 2021). Some are sceptical about whether an empirical study of ethics is even possible (e.g., Brundage, 2014). Our review demonstrates that practical ethics can potentially enable HEIs to stay up to date with these developments, which shifts the focus away from adherence to abstract rules and principles, towards the processes involved in real-life use of LA tools. More studies that feature practical ethics can help shape institutional ethics policies that would focus not only on how to avoid harm when engaging with LA tools, but also on how, through ethical engagement, the potential of these tools can shine in creating opportunities and in fostering human nature.

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This case study reviewed the following 10 studies:

Study 1: Rienties, B., Herodotou, C., Olney, T., Schencks, M., & Boroowa, A. (2018). Making sense of learning analytics dashboards: A technology acceptance perspective of 95 teachers. *The International Review of Research in Open and Distributed Learning, 19*(5). https://doi.org/10.19173/irrodl.v19i5.3493

Study 2: Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., & Hlosta, M. (2019a). A large-scale implementation of predictive learning analytics in higher education: The teachers' role and perspective. *Educational Technology Research and Development, 67*, 1273–1306. https://doi.org/10.1007/s11423-019-09685-0

Study 3: Herodotou, C., Hlosta, M., Boroowa, A., Rienties, B., Zdrahal, Z., & Mangafa, C. (2019b). Empowering online teachers through predictive learning analytics. *British Journal of Educational Technology, 50*(6), 3064–3079. https://doi.org/10.1111/bjet.12853

Study 4: Herodotou, C., Naydenova, G., Boroowa, A., Gilmour, A., & Rienties, B. (2020a). How can predictive learning analytics and motivational interventions increase student retention and enhance administrative support in distance education? *Journal of Learning Analytics, 7*(2), 72–83. https://doi.org/10.18608/jla.2020.72.4

Study 5: Herodotou, C., Rienties, B., Hlosta, M., Boroowa, A., Mangafa, C., & Zdrahal, Z. (2020b). The scalable implementation of predictive learning analytics at a distance learning university: Insights from a longitudinal case study. *The Internet and Higher Education, 45*, 100725. https://doi.org/10.1016/j.iheduc.2020.100725

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Study 7: Herodotou, C., Maguire, C., McDowell, N., Hlosta, M., & Boroowa, A. (2021). The engagement of university teachers with predictive learning analytics. *Computers & Education, 173,* 104285. https://doi.org/10.1016/j.compedu.2021.104285

Study 8: Hlosta, M., Herodotou, C., Bayer, V., & Fernandez, M. (2021). Impact of predictive learning analytics on course awarding gap of disadvantaged students in STEM. In I. Roll, D. McNamara, S. Sosnovsky, R. Luckin, & V. Dimitrova (Eds.), *Proceedings of the 22nd International Conference on Artificial Intelligence in Education* (AIED 2021), 14–18 June 2021, Online from Utrecht, The Netherlands (Part I, pp. 190–195). Springer. https://doi.org/10.1007/978-3-030-78270-2_34

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