Artificial Intelligence: **Learning Analytics in Education**

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"ΨΗΦΙΑΚΟΙ ΜΕΤΑΣΧΗΜΑΤΙΣΜΟΙ ΚΑΙ ΤΕΧΝΗΤΗ ΝΟΗΜΟΣΥΝΗ: Προκλήσεις στο Σύγχρονο Εκπαιδευτικό Περιβάλλον"

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Topics *(Artificial Intelligence for Tutoring Systems, Technology-supported Learning, Learning Technologies, Learning Analytics, Adaptive learning)*

Abstract

- Research areas
- Contributions

Keywords

- Artificial intelligence (AI), **Learning analytics** (LA), **Ethics**, **Instructional design**, Teaching **guidance** strategies, Higher education, Co-design, Learning analytics **adoption**, **Teachers**’ and **Students**’ perceptions, **Participatory** design, **Human-centered** design; **Actionable**; K-12 education; Ethnography, **Mixed methods**

Topics

- ✓ Introduction
- ✓ Background
- ✓ Ethical Issues in Adopting Artificial Intelligence & Learning Analytics
- ✓ The Impact of LA Guidance on Student Performance and Self-Regulated Learning Skills
- ✓ Students' Perceptions of Adopting AI/LA
- ✓ K-12 Teachers' Acceptance and Resistance Perceptions of AI/LA Adoption
- ✓ Conclusions – Future Work

I. INTRODUCTION

Research Areas

- ✓ Review of AI/LA
- ✓ Ethics
- ✓ Impact of AI/LA based Guidance
- ✓ Adoption of AI/LA

It is the epoch of big data, social networks, and cloud computing. Every piece of data is captured and leaves a digital trail (Siemens & Long, 2011), 'increasing the volume, variety, velocity and veracity of student data' (Prinsloo & Slade, 2017, p.8).

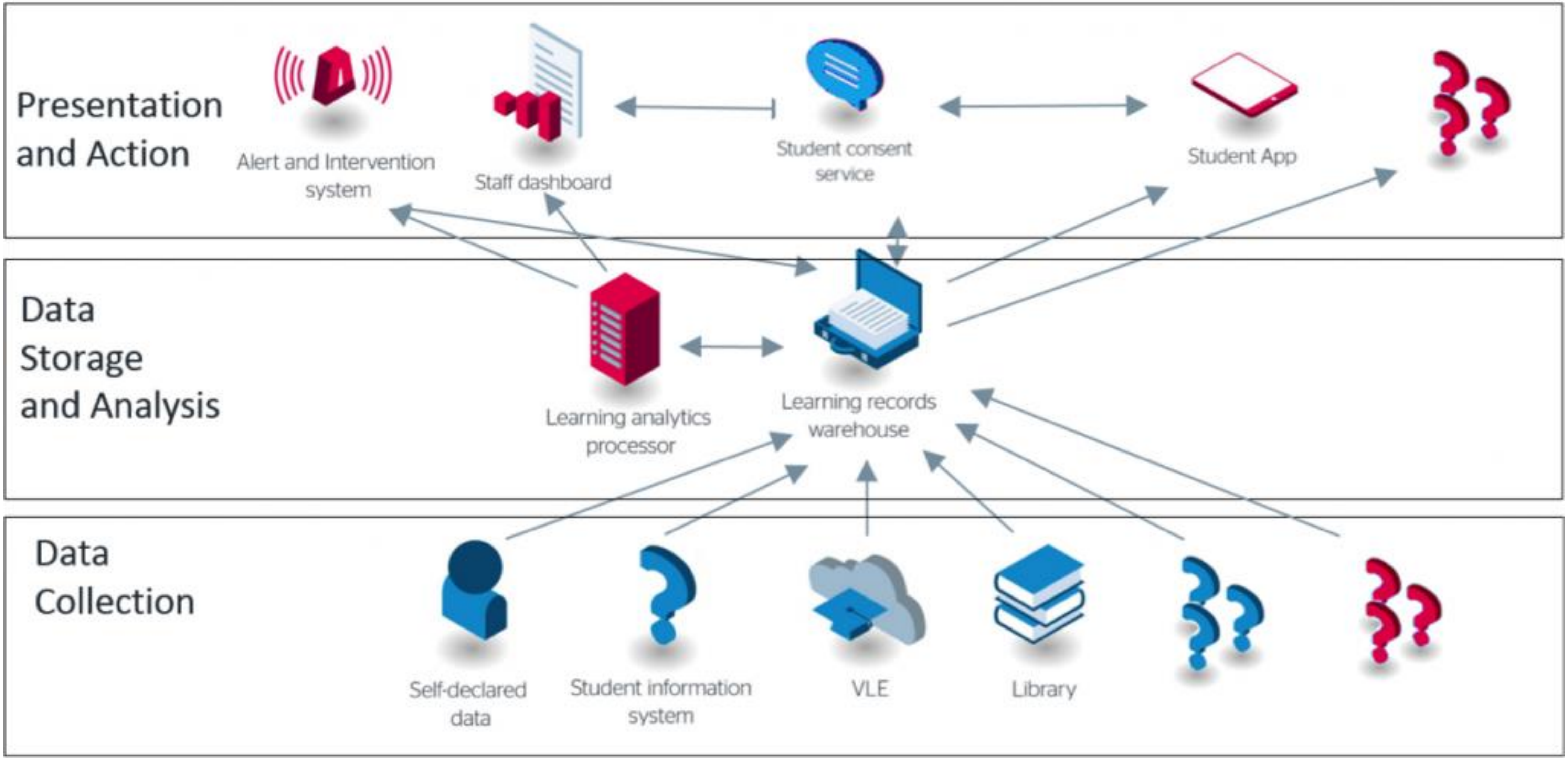
Academic analytics is concerned with data analysis at the institutional or national level, whereas LA is concerned with the learner process, course, or faculty level (Olmos & Corrin, 2012)

Methods

Table 1. Summary of key terminology related to the research (based on Twining et al., 2017)

	Level	
	Theoretical stance: Epistemology	Meaning is culturally defined
Approach	**Methodology**	**Qualitative** (Interpretivist)
	Ethnography Design	emphasizes *i*nductive reasoning
	Techniques for collecting data	Interview; Observation; Document analysis
	Instruments (specific data collection tools)	Interview schedule; Observation sheets
	Analysis	**Phenomenography** (how the data are processed to answer the RQs)

Learning Analytics



Research Questions

- ✓ First RQ: What, why, and for whom is critical in AI/LA?
- ✓ Second RQ: What are the methods for effectively implementing AI/LA?
- ✓ Third RQ: What are the difficulties in AI/LA adoption?

II. BACKGROUND

Introduction

- ✓ The results demonstrated that LA is an *interdisciplinary field* and that developing efficient techniques is a new research challenge for the educational community. This study discusses the results of defining and analyzing five conceptual dimensions**: the object of analysis, technology, objectives, stakeholders, and ethics.**
- ✓ LA is a discipline at the intersection of data analysis and learning sciences, allowing students to reclaim decades of educational research as a valuable daily practice (Akhtar et al., 2017).
- ✓ EDM, Teaching & Learning Analytics

Object of analysis

- Students are sometimes reluctant to provide data for LA purposes (Ifenthaler & Schumacher, 2016). Furthermore, big data does not equal meaningful insights, so we must select meaningful data types to ensure a good *signal-to-noise* ratio.

Passive data is collected using sophisticated tools that do not require input from learners (Akhtar et al., 2017)

Assessment data
LMS & forum participation
Understanding of learning techniques
Time management
Collaboration
Satisfaction

Data processing technology

TABLE 1 A sample of LA specialized lines of research and studies

LA line	Description
Social LA (Martin, Nacu, & Pinkard, 2016)	Provides methods to study, understand, and evaluate the use of social media for learning by content and network analyses of social media texts and networks.
Smart LA (Giannakos, Sampson, & Kidziński, 2016)	Enables the analysis of valuable information gathered from heterogeneous sources and ways to deploy personalized and smart learning.
Video LA (Giannakos et al., 2016)	Transforms video streaming into useful knowledge to improve learning based on videos.
Ubiquitous LA (Mouri & Ogata, 2015; Peña-Ayala, 2015)	Analyses learner traits and contextual data to depict interactions between learners and their contexts, and learners with context based learning materials.
Visual LA (Hillaire, Rappolt-Schlichtmann, & Ducharme, 2016)	Supports pedagogical decisions by interactive visualizations that claim information design to acquire, parse, filter, mine, depict, and interact with a data collection.
Multimodal LA (Andrade, Delandshere, & Danish, 2016; Ochoa & Worsley, 2016)	Gathers multimodal information in human activity through data-capturing methods and sensing technologies.
Dispositional LA (Tempelaar, Rienties, & Nguyen, 2017)	Combines learning log data with learner data (e.g., experiences, social relations, values, and attitudes that influence the engagement with learning).
Open LA (Muslim, Amine, Mahapatra, & Schroeder, 2016)	Considers diverse actors with specific goals that demand a broad range of data from several settings to elicit knowledge and gain insight into learning processes.

Data processing methods are concerned with the **backend of LA**, whereas input data is meaningless unless processed.
ML interprets big data instead of humans using supervised (regression, classification) or unsupervised (clustering, association) models.
Natural language processing techniques are used to analyze and discover course concepts, such as qualitative data collection and text analysis, to uncover hidden patterns within online student comments, essays, and discussions.

Target of intervention

- From a pedagogical standpoint, we investigate the benefits of the **front end** of LA, such as personalized learning, student engagement and commitment, motivation, self-regulated learning (SRL), and actionable feedback.

Monitoring and on-time feedback
Differentiated teaching
Teaching adaptation
Learning performance
Participation - engagement

Stakeholders

About LA stakeholders, the focus in the relevant literature is on:

- **Student** level: triggers students' *SRL* skills, interaction, and retention; respects diverse ways of learning (*formative* assessment, *differentiated* learning).
- **Instructors** level: course monitoring systems, *learning design*, *actionable* decision-making, adapting teaching strategy, quality of courses; Increase the teachers' analytical skills to implementing LA activities.
- **Institution**-level (policymakers, administrators, researchers): *resource allocation* and evidence-based decision-making; Institution's autonomy and accountability.

The findings revealed that most LA research study participants (n = 96) were from **HEI**, which could be because higher-education students are more accessible to researchers. Other studies (n = 18) looked at secondary school students.

III. ETHICAL ISSUES IN ADOPTING AI/LA

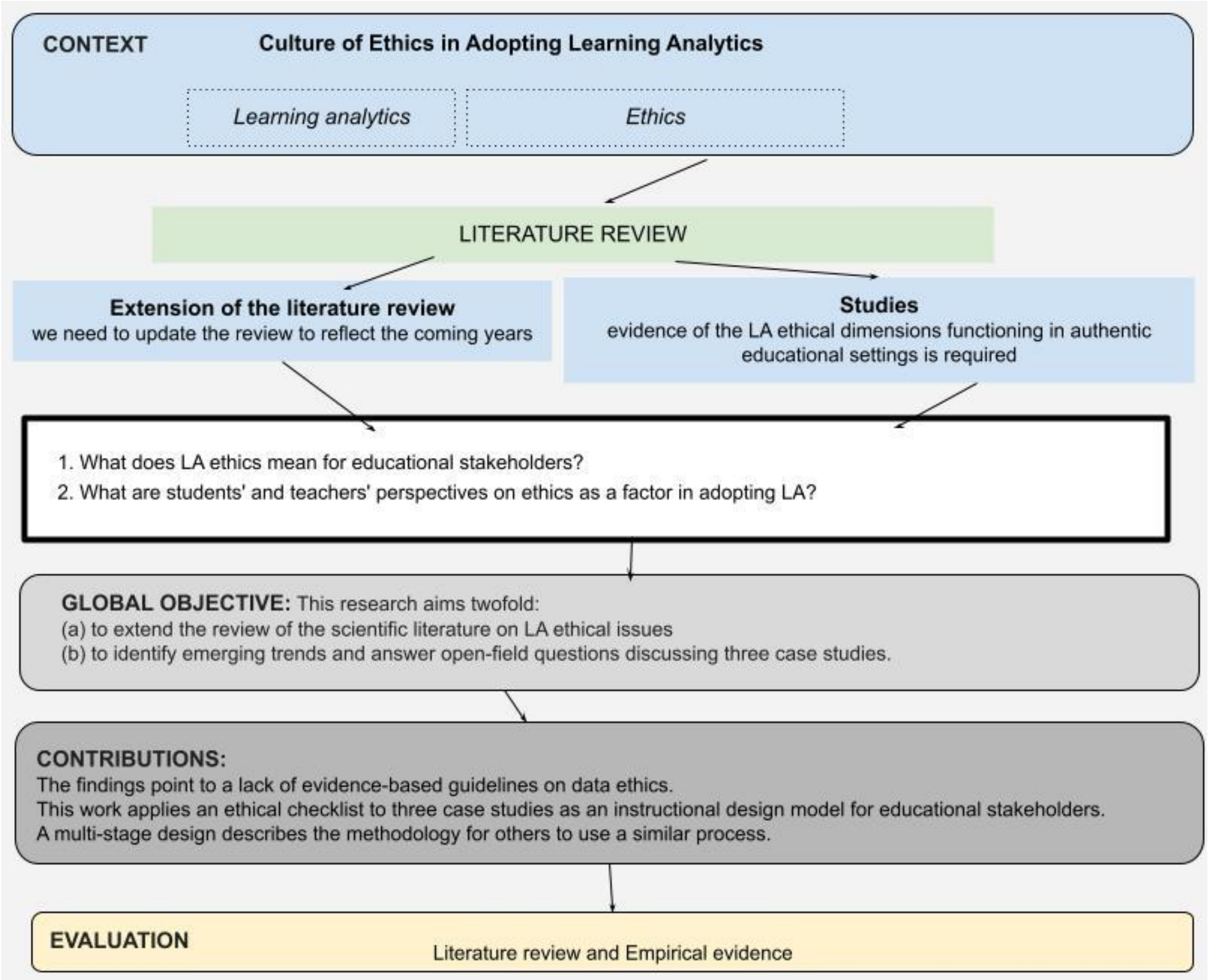


Figure 1. A diagram depicting the context, objectives, and contributions of the study

Ethics - Types of ethics

Ethics is a framework of moral principles that is concerned with what is right for individuals and society (Gray & Boling, 2016).

- Deontological
- Consequentialist
- Virtue
- Applied ethics

PANDORA checklist (Tzimas & Demetriadis, 2021) – adoption of LA
https://bit.ly/3zT5lyN

Cardinali et al. (2015) defined ethics as a moral code of norms that exist in society externally to a person, depending on culture and time.

Contradictions in the Literature

- ✓ Technological (‘the current legal system is immature in relation to privacy and ethics concerns in analytics’)
- ✓ Pedagogical (SRL vs surveillance)
- ✓ Policy contradictions (ethics differs around the world)

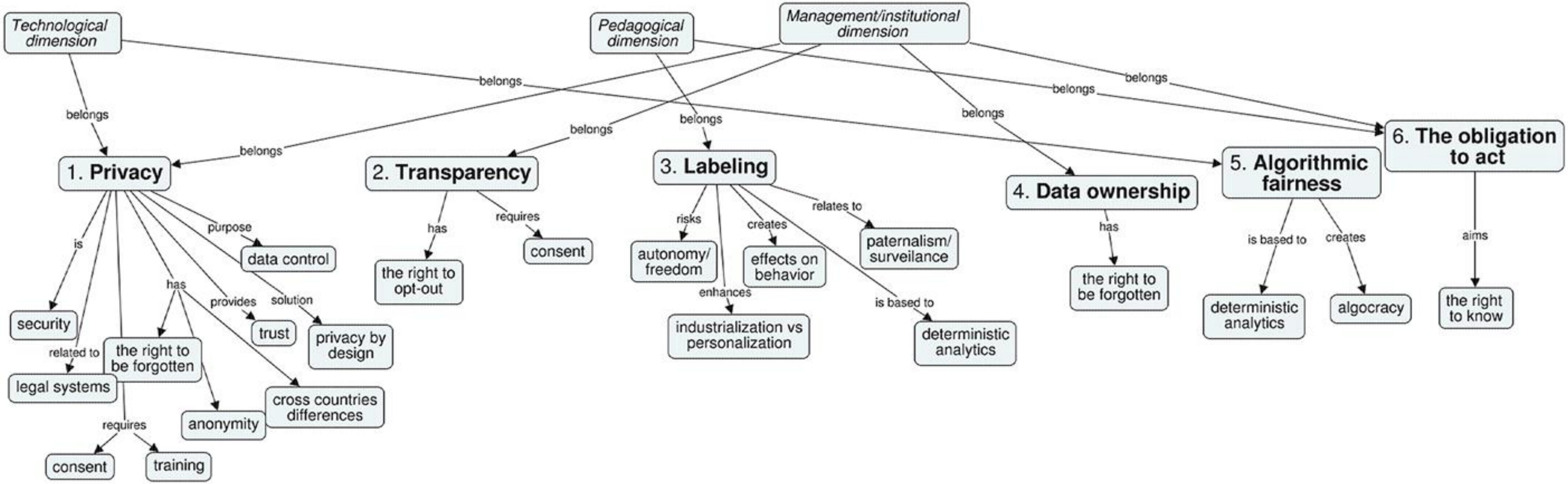
Analytics focuses on already existing data, while education and learning should enhance innovative ideas and approaches.

Antagonistic Viewpoints

Issue	*Description*
Stakeholders	
1.1 Instructors	***Ethical responsibilities vs. interventionism***
1.2 Learners	***Need support vs. skepticism***
1.3 Institutions (Academic Analytics)	**Learning analytics vs. Student perspective**
1.4 Decision-makers & data-controllers	**Data-driven algorithms: deterministic vs probabilistic**
1.5 Governance	**Different laws vs. good communication**
Benefits - Drawbacks	
2.1 Support vs. bias, privacy	**Positive vs. ineffective interventions & minimalism vs quality**
2.2 Intellectual freedom vs. surveillance	***Autonomy vs. paternalism***
2.3 Learning's innovation vs. Analytics' evaluation of what exists in data	**Educational viewpoint vs. data mining perspective**
Rights vs. Obligations	
3.1 Right to	**Be forgotten, know, restrict processing, opt-out**
3.2 Obligation to	**Act, do the best**
Technology vs. Regulations	**Dynamic vs. static**
Ethics vs. Law	**Moral conventions vs. Legal Norms**
Student-oriented vs. intervention oriented	**Active agents vs. Passive recipients**

Ethical Issues in AI/LA

Concept and relations mapping of key ethical issues



Data Privacy and Ownership

- A broad legal definition of privacy is a **human's right to define access to his or her data** and, in the context of learning, to protect the identity of a learner to **prevent abuse** (Dyckhoff, Sielke, Bultman, Chatti, & Schroeder, 2012).
- The boundaries and meaning of *what is private differ among cultures* (Willis et al., 2016).
- In the US, the collected data belongs to the data collectors, while in the European Union (EU), personal data belongs to the individual from whom the data is extracted (Haythornthwaite, 2017).
- Trust.

***Zuckerberg's** statement: "Privacy is over!"*

Data ownership

- Ownership refers to data collected, the analytics used, and the output of the analytics

- Who owns the data and the prognosis models?
- Right to be forgotten

‘more educational data does not always make better educational data’ (Ifenthaler & Tracey, 2016, p. 1).

Transparency and the Duty to Act

- ✓ Transparency involves a *well-informed choice to opt-in or opt-out*. From a pedagogical perspective, this means providing students with **self-control** and self-observation
- ✓ **Opting out** may leave significant gaps in the data set and reduce the efficiency of LA systems for other learners
- ✓ Students are conservative in sharing personal data and learners would share more data if the LA task transparently provided *meaningful information (impact)*.
- ✓ *InBloom case*
- ✓ Stichting Snappet case

- ✓ **Obligation of knowing** http://bit.ly/2GyY7as (*Murray's learning analytics-inspired system*)

'The probability that the students will disclose required information is higher if they expect the benefits to be greater than the risk' (Ifenthaler, & Schumacher, 2016, p. 935).

Labelling-Paternalism

- Profiling, surveillance

*Analytics provides a **black box** that determines 'who is going to fail before they have even begun' (Beattie et al., 2008, p. 1).*

*Learn from past experiences without their student profile being 'etched like a **tattoo** into their digital skins' (Mayer-Schonberger, 2011, p. 14).*

Fairness in Algorithms

- **Misinterpretation & Biases**
- **Algocracy**
- Increasing the level of *privacy* reduces the *accuracy* of the LA outcomes (Gursoy et al. 2017)
- Misinterpretation of data (**human error**), and the adherence to misleading patterns (***machine-based*** *error*)
- For instance, wealthy schools typically have computerised education, so the data and insights extracted from LA may not accurately reflect the *general population*.

'not everything that can be counted counts; and not everything that counts, can be counted'

'reduction of the individual student to a simple metric' (Arnold & Sclater, 2017, p. 2).

'analytics is perceived by some as an engine for controlling and correcting behaviours'

Word list sorted by weight

Stakeholder	Issue	Other
Learners (127)	Privacy (100)	Policy (33)
HE Institutions (88)	Obligation to act	Legal (11)
Teachers (21)	Profiling (10)	IoT (10)
Instructional designers (14)	Transparency (8)	Moral (5)
Librarians (2)	Data ownership (8)	GDPR (5)
Parents (2)	Surveillance (7)	

Research and open-ended questions extracted from the literature

Paper	Questions / Key perspective
Avella et al. (2016)	What are the challenges of using LA in education?
Pardos et al. (2016)	Transparency: what data is being collected, how is it being represented?
Drachsler & Greller(2016)	If there is a computational model developed from a collection of data traces in a system, can a student still opt-out of such a model?
Pardo & Siemens (2014)	How are privacy addressed in other contexts? Who owns the data: the institutions, the students, the companies using them?
Scholes (2016)	Should a decision-maker sort students on the basis of group-risk statistics?
Sclater (2016)	In which situations should students be asked for consent to the collection of their data for analytics?
Arnold & Sclater (2017)	Would you be happy for data on your learning activities to be used if it kept you from dropping out?
Siemens (2013)	Who has access to analytics? Should a student be able to see what an institution sees? How long does a university keep those data?
Beattie et al. (2008)	There are questions in the analytics about who owns individual learners' data?

The ethical issues overlap each other in the literature (Venn diagram)

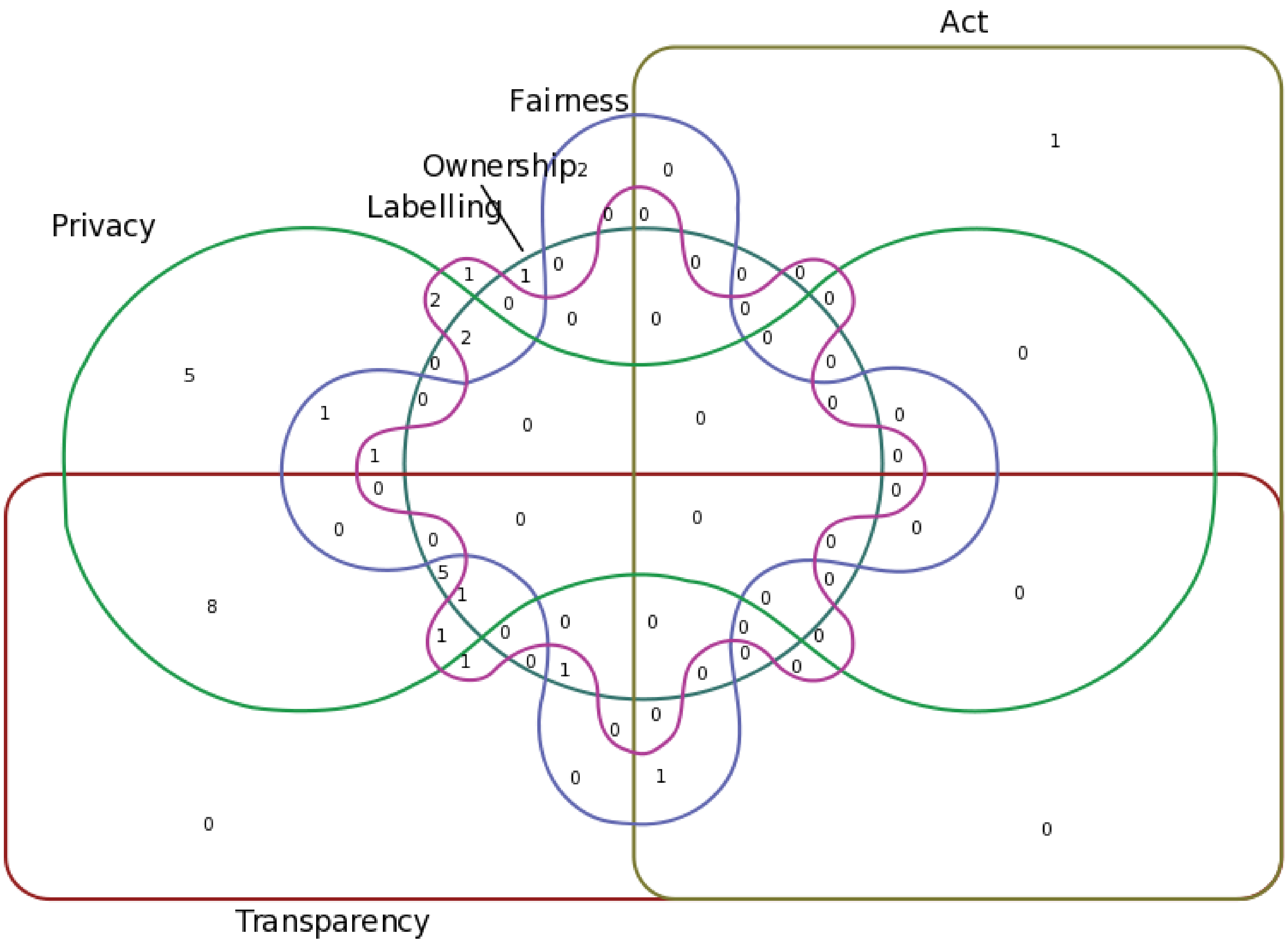


Table 7 Instructional theory and methods

Instructional theories and methods	References
SRL instructional design theory (*n* = 18)	Ott, Robins, Haden, & Shephard, 2015; Lu, Huang, Huang, & Yang, 2017; Pardo et al., 2017; Tabuenca, Kalz, Drachsler, & Specht, 2015; Park & Jo, 2015; Gewerc, Rodriguez-Groba, & Martinez-Pineiro, 2016; Papamitsiou, & Economides, 2015; Martin & Whitmer, 2016; Petropoulou, Kasimatis, Dimopoulos, & Retalis, 2014; Stefan, Moldoveanu, & Gheorghiu, 2016; Ruipérez-Valiente, Muñoz-Merino, Leony, & Delgado Kloos, 2015; Mazarakis, 2014; Chou et al., 2017; Melero, Hernández-Leo, Sun, Santos, & Blat, 2015; Softic et al., 2014; Olmos & Corrin, 2012; Kim, Park, Yoon, & Jo, 2016; Gasevic, Mirriahi, Dawson, & Joksimovic, 2017.
Engagement instructional outcome (n = 16)	Kim et al., 2016; Stefan et al., 2016; O'Riordan, Millard, & Schulz, 2016; Olmos & Corrin, 2012; Smith, Lange, & Huston, 2012; Tempelaar, Rienties, & Giesbers, 2015, Pursel, Zhang, Jablokow, Choi, & Velegol, 2016; Davidson & Candy, 2016; Lu et al., 2017; Pardo et al., 2017; Ott et al., 2015; Papamitsiou, & Economides, 2015; Xie, Zhang, Nourian, Pallant, & Hazzard; 2014; Lan, Studer, Waters, & Baraniuk, 2014; Sedrakyan, Snoeck, & De Weerdt, 2014; Ma, Han, Yang, & Cheng, 2014.
Feedback instructional method (n = 14)	Gibson & de Freitas, 2016; Gasevic, Dawson, Rogers, & Gasevic, 2016; Tabuenca et al., 2015; Lan et al., 2014; Chou et al., 2017; Ott et al., 2015; Liu et al., 2016; Kim et al., 2016; Poitras, Naismith, Doleck, & Lajoie, 2016; Firat, 2017; Tempelaar et al., 2015, Ifenthaler & Widanapathirana, 2014; Kennedy, Ioannou, Zhou, Bailey, & O'Leary, 2013; Lu et al., 2017.
Active learning instructional method (n = 10)	Gasevic et al., 2016; Mazarakis, 2014; Kotsiantis, Tselios, Filippidi, & Komis, 2014; Petropoulou et al., 2014; Liu et al., 2016; Xie et al., 2014; Gewerc et al., 2016; Xing, Guo, Petakovic, & Goggins, 2015; Hernández-García, González-González, Jiménez Zarco, & Chaparro-Peláez, 2016; Park & Jo, 2015.
Motivational design (ARCS instructional model) (n = 6)	Tempelaar et al., 2015; Lan et al., 2014; Sedrakyan et al., 2014; Davidson & Candy, 2016; Lonn, Aguilar, & Teasley, 2015; Mazarakis, 2014.

PANDORA - a proposed checklist (Privacy)

*For **institutions or instructional designers,** the institutions should establish security, data management, data minimisation, and control.*

1.1.A. Be clear about who has specific access to the recorded data.

1.1.B. Develop contracts with externals vendors in ways that respect and manage privacy.

1.1.C. Apply the GDPR.

1.1.D. Apply authentication and authorisation techniques.

1.1.E. Hire a data protection officer who will be responsible for compliance with the rules through learning.

1.1.F. Ensure the instructional designer's ethical training and awareness of ethical concerns at all stages of the LA process.

*For **learners**, consent should be guaranteed; learners should be able to opt-out without adverse consequences, and purposeful LA should be ensured for learners.*

1.2.A. Anonymise students' personal data.

1.2.B. Inform students about the analysis of their learning data.

Without solving this issue with the data management layer, the ***harm*** is that LA projects may be cancelled and stakeholders will not trust the LA services.

Autonomy

2.1. For **learners and teachers**, check for intellectual freedom, ensure individuality, and avoid labelling and surveillance.

2.1.A. *Guarantee that the feedback from instructors does not <u>discourage</u> students.*

2.1.B. *Do not use <u>labels</u> for students that hinder their education and well-being.*

2.1.C. *Follow a specific instructional theory (e.g., <u>SRL</u>) to model students as active users.*

2.1.D. *Respect <u>diverse</u> characters and different learning paths and needs (differentiated learning).*

With regard to *harm*, learners fear <u>bias</u> and stigma and they accept untrusted categorisation; they are consequently passive recipients. They also feel discouraged and that their academic freedom is at risk, both of which limit their learning expectations.

Algorithmic fairness

3.1. For **institutions**, the quality and objectivity of data and models, the absence of interventionism, and the utilisation of learner-oriented approaches. The most prominent methods are as follows:

- ***3.1.A.*** *Take into account that a student's performance has a temporal and dynamic character (formative assessment).*
- ***3.1.B.*** *Inform data administrators about the processing principles that are employed (e.g., predictive models, ML algorithms).*
- ***3.1.C.*** *Make biases explicit in order to overcome them.*
- ***3.1.D.*** *Make use of representative data.*

3.2. For **teachers**, the possibility of a human or machine-based error exists, so misdirected interventions should be considered.

- ***3.2.A.*** *Explain to students how the models produce reliable outcomes and why they have been selected for intervention.*
- ***3.2.B.*** *Use SRL to trace data and analysis to extract insights into the reasons for variation in students' behaviour.*
- ***3.2.C.*** *Take into account that the features in a predictive model are usually limited in accordance with the training vector space.*

3.3. For **learners**, learning is not a deterministic procedure.

- ***3.3.A.*** *Inform students that LA should not be the only source of decision-making.*
- ***3.3.B.*** *Train learners to interpret the results and visualisations of LA.*

Without addressing this issue, the *harm* for learners is that they will lose their autonomy. Institutions make predictions without understanding the model, thereby reducing the accuracy of the LA outcomes and creating biases in data interpretation.

Duty to act

4.1. For **learners**, the right to know should be applied as a moral and legal necessity to act.

4.1.A. *Inform students about their progress and provide <u>timely support</u>.*

4.1.B. *<u>Encourage self-interventions</u> for learners.*

4.2. For **teachers and institutions**, accurate and timely interventions should be provided.

4.2.A. *Take into account the <u>predictive value of LA</u>.*

4.2.B. *Use <u>early alert</u> systems to achieve positive student motivation.*

4.2.C. *Do not ignore ethics (e.g., follow a guideline).*

4.2.D. *Inform instructional designers if the intervention is more harmful than beneficial to the welfare of the learner.*

When the above-mentioned aspects are violated, first, the *harm* for learners is that timely support is not provided. Second, communication and <u>trust</u> among stakeholders decrease. Finally, it is <u>costly</u> for a student to study and withdraw from education in terms of fees, time, and energy spent.

Openness and transparency

5.1. For **learners**, the possibility for informed and voluntary consent should be provided.

5.1.A. A student can see what an institution sees.

5.1.B. A student can opt-out of (or not opt-in to) a data model.

5.1.C. Students' data should never be shared without their informed consent.

5.1.D. The institution must appoint a person to handle complaints about LA research.

5.2. For **institutions**, purpose limitation should be imposed and their awareness of data use and algorithms should be ensured.

5.2.A. Ensure that student data will not be sold.

5.2.B. Ensure that information is used for learning and not for other purposes.

5.2.C. Define the data that is being collected, why it is being collected, and how it is being visualised.

5.2.D. Define who has accountability for the overall LA procedure.

5.2.E. Encourage academics to use the LA system in a manner that is consistent with the intentions of the course designers.

If this issue is ignored, learners will become stressed and demotivated to participate in providing their data for analysis.

Resolve the data ownership

6.1. **Learners** must have the right to be forgotten. Following a user-centric design aims to place students in control of their data.

6.1.A. *The duration for which data and outcomes will be stored is defined.*

6.1.B. *Students have the right to correct inaccurate information and remove irrelevant information.*

6.1.C. *Students can control how their data is used and shared.*

6.2. **Institutions** should take on the responsibility and control of data and data processing.

6.2.A. *Issue specific data access permissions to each stakeholder.*

6.2.B. *Take into account the different laws between countries and the different approaches among institutions.*

6.2.C. *Handle information about the learners securely.*

If this issue is not resolved, the *harm* is that learners will not trust the LA services and will hide their learning data.

Stakeholders

All stakeholders (i.e., students, instructors, institutions, and industrial agents) should be involved and communicate with each other. The instructional methods for this issue are as follows:

7.1.A. Inform learners about their responsibility for self-intervention.

7.1.B. Provide teachers and data administrators with sufficient training in LA.

7.1.C. Establish channels of communication between stakeholders (e.g., IRBs or parents as partners in learning).

7.1.D. Establish data ethics teams within institutions with experts in data ethics and representatives of faculties and students.

7.1.E. Train educational technology staff in analytical skills (e.g., in using algorithms and statistics to design and implement LA initiatives).

7.1.F. Ensure that LA stakeholders and interdisciplinary practitioners (e.g., teachers and librarians) have professional codes of ethics (e.g., library ethics).

Without considering this issue, the *harm* is that the stakeholders will have no responsibility or means of communication. Moreover, students will be engaged as recipients of (and not as collaborators in) interventions and LA services. Thus, overall, an asymmetrical power relationship will exist between data gatherers and the data object.

IV. The Impact of AI/LA based Guidance on Student Performance and Self-Regulated Learning Skills

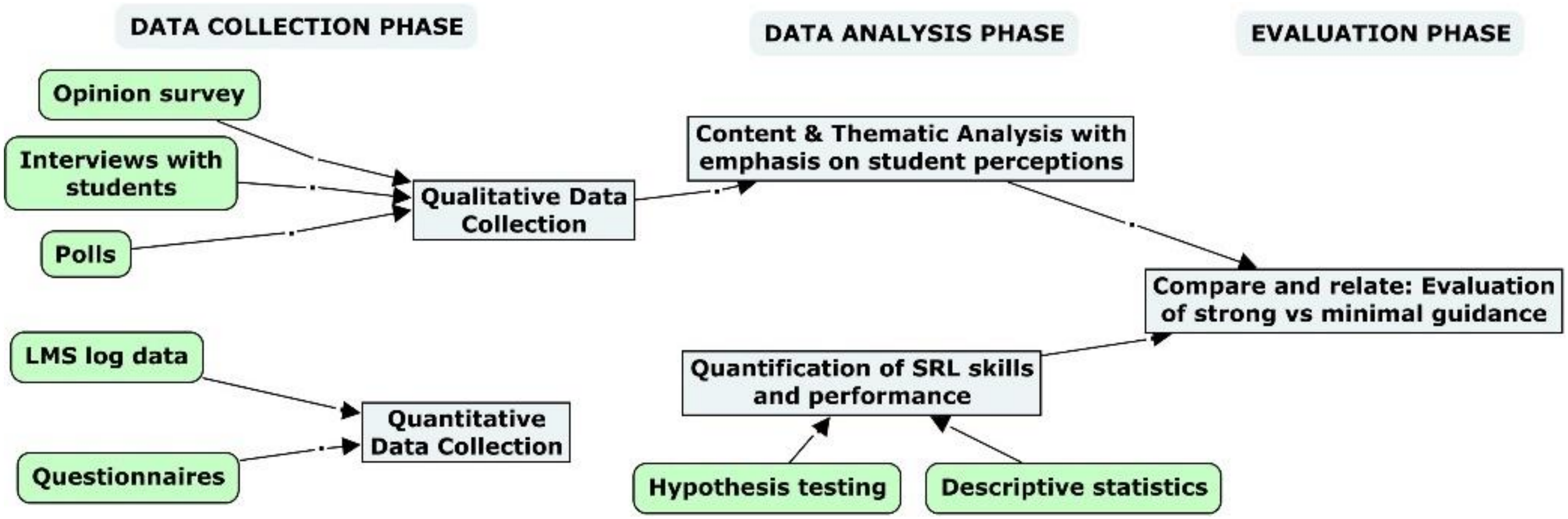
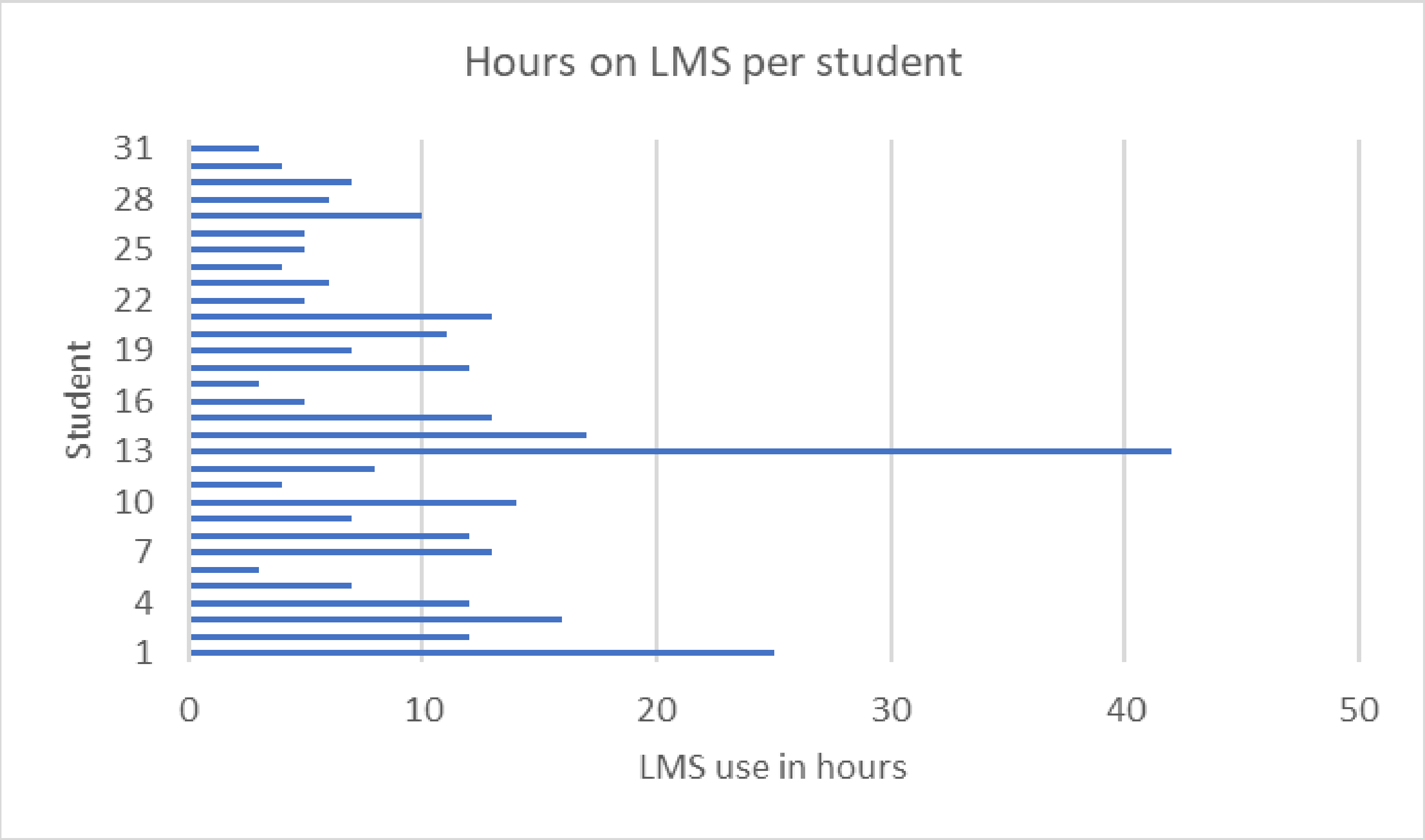


Figure 5. Diagram of the triangulation design procedures used in this research

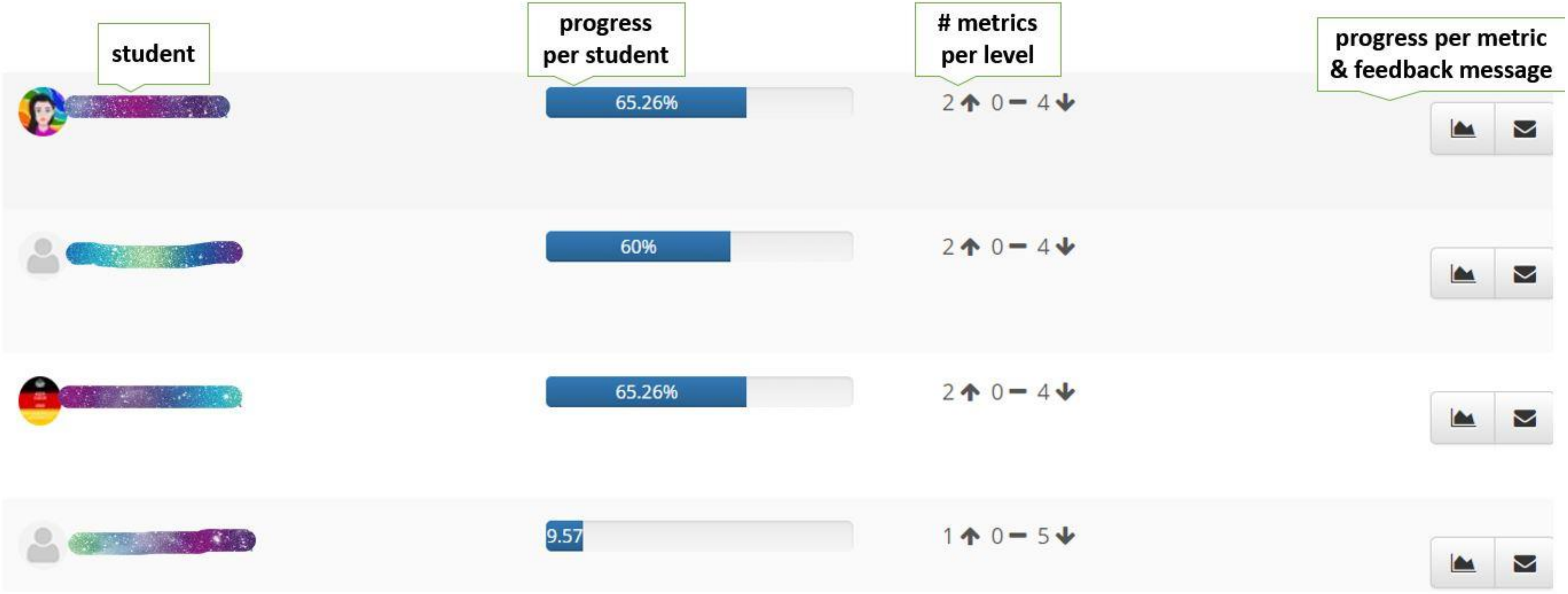
Figure 1. Personalized feedback with visualizations for mirroring

Table 2. The t-test results of the experimental (LG) and control (NG) groups for performance

Group	N	Mean	SD	t	p
Experimental	31	**6.08**	2.62	1.077	0.287
Control	32	**5.49**	1.60		



Learning Analytics	
Criterion	*Percentage*
First exercise's grade	100%
Second exercise's grade	72.73%
Forum participation	7%
Links on LMS	4%
Project grade	100%
Timely submission	20%



student
progress per student
metrics per level
progress per metric & feedback message
65.26%
2 0 4
60%
2 0 4
65.26%
2 0 4
9.57
1 0 5

Table 2. Performance *t*-test results for the experimental (SG) and control (MG) groups.

Group	**N**	**M**	**SD**	**t (91)**	***p***
Experimental	47	**7.22**	2.71	2.75	0.007
Control	46	**5.28**	3.95		

Table 3. Independent samples t-test prequestionnaire results between the groups.

SRL Skills	SG (N = 38)	MG (N = 31)	*p*	t (67)
	M (SD)	M (SD)		
Metacognitive activities before learning	3.47 (1.33)	3.19 (1.22)	0.370	0,90
Metacognitive activities during learning	3.50 (1.20)	3.29 (1.27)	0.485	0.70
Metacognitive activities after learning	2.90 (1.29)	3.06 (1.15)	0.602	−0.52
Time management	3.21 (1.11)	3.22 (1.23)	0.957	−0.54
Environmental structuring	5.42 (1.64)	5.09 (1.61)	0.415	0.82
Persistence	3.10 (1.35)	2.83 (1.09)	0.379	0.88
Help seeking	3.34 (1.75)	3.16 (1.45)	0.647	0.46

Table 4. Post-test questionnaire analysis: ANCOVA results between the groups.

SRL Skills	SG (N = 38)	MG (N = 31)	ANCOVA
	M (SD)	M (SD)	
Metacognitive activities before learning	5.21 (1.50)	4.20 (1.17)	$F[1,66] = 8.375$, $p = 0.005$ *, $\eta p2 = 0.113$
Metacognitive activities during learning	4.21 (1.31)	4.09 (1.16)	$F[1,66] = 0.001$, $p = 0.975$, $\eta p2 = 0.000$
Metacognitive activities after learning	4.93 (1.38)	3.70 (1.20)	$F[1,66] = 27.398$, $p = 0.000$ *, $\eta p2 = 0.293$
Time management	5.34 (1.12)	4.12 (1.28)	$F[1,66] = 22.502$, $p = 0.000$ *, $\eta p2 = 0.254$
Environmental structuring	5.35 (1.51)	4.75 (1.54)	$F[1,66] = 2.521$, $p = 0.117$, $\eta p2 = 0.037$
Persistence	5.21 (1.52)	3.70 (1.21)	$F[1,66] = 22.181$, $p = 0.000$ *, $\eta p2 = 0.252$
Help seeking	5.17 (1.43)	3.80 (1.54)	$F[1,66] = 25.266$, $p = 0.000$ *, $\eta p2 = 0.277$

* Significant difference at the 0.05 level

- When **strong guidance** was applied, the results indicated *increased final grades and SRL skills* (metacognitive activities, time management, persistence, and help-seeking).

V. Students' Perceptions of Adopting AI/LA

Table 5. Summary of student opinion survey descriptive statistics (N = 34).

Survey Statements	M	SD
LA quality		
LA was simple to understand	5.0	1.8
LA helped increase participation	4.9	1.6
The guidance for using LA was adequate	5.0	1.6
There was a sufficient interpretation of the LA	5.0	1.2
Effectiveness of LA on SRL skills		
I prefer LA use in the learning process over the traditional one	4.7	1.6
I would like LA to be applied to other courses	4.9	1.8
LA resulted in putting more effort into the course	4.4	1.7
LA made me feel I had better control over the learning process	4.6	1.9
Student satisfaction		
LA was an enjoyable learning experience	4.9	1.5
LA had pedagogical value	4.5	1.5
LA has boosted my confidence	4.4	1.5
LA maximized my motivation to engage in the course	4.8	1.5
Motivation to use		
There was an understandable explanation using the LA	5.0	1.2
A discussion was conducted to explain the LA results	5.0	1.6
LA helped me be aware of the course	5.2	1.3

Table 6. Interview results—Qualitative themes.

Theme	Sample Evidence Quotes	Freq. (n = 36)
Behavior change	The RYG alert awakened me, and I decided to start doing exercises (ST3)	52%
Guidance	My grades were below the class average; therefore, this comparison changed my study habits (ST17)	45%
Help seeking	LA services encouraged me to ask for support (ST32)	39%
Motivation	LA motivated me to keep trying (ST5)	34%
Involvement	LA should be tailored to my needs (ST15)	17%
Time management	LA gave me study orientation, e.g., time management (ST11)	17%
Persistence	LA resulted in putting more effort (ST29)	16%
Stress	LA intrigued and stressed me creatively (ST26)	14%

IV. K-12 Teachers' Acceptance and Resistance Perceptions of Learning Analytics Adoption

Notes for Practice

- The degree of LA adoption across schools remains *limited*, and teachers who adopt LA do not engage with it consistently.
- The factors *facilitating* LA adoption are performance expectancy, social influence, and feelings.
- The factors *inhibiting* the adoption of LA are effort expectancy, self-efficacy, facilitating conditions, and culture change.
- Future research should investigate the *implementation and confirmation stages* to determine the viability of the LA adoption process.

- “Using the Unified Theory of Acceptance and Use of Technology (**UTAUT**) as a theoretical model, which factors explain the adoption of LA in schools? How do teachers describe their motivation and readiness for LA adoption?”

Table 1. Focus Group Questions and their Relationship to the UTAUT

Code	Question
[Q1]	Do you think LA positively impacts your teaching practice? In what ways? (Performance expectancy)
[Q2]	How much time are you willing to invest in LA? (Effort expectancy)
[Q3]	Do you need any help understanding the specific features of LA? (Self-efficacy)
[Q4]	Who would you like to give you this help (Facilitating conditions)? For example, emails from the manager (Social influence)?
[Q5]	What feelings does LA provoke in you? Why? (Anxiety)
[Q6]	Do you have any concerns about its future use? (Anxiety)
[Q7]	Do you intend to use LA in the future? Explain. (Behavioral intention)
[Q8]	What are the critical factors for LA adoption? What may be stopping your school from adopting LA?
[Q9]	Is there any additional information that would be important to obtain from you?

Table 2. Summary of Teacher Perception Survey Descriptive Statistics (N=73)

Items used to measure teaching staff expectations regarding LA adoption	**M**	**SD**
Perceived usefulness (performance expectancy)		
I believe that the instructional technique of LA has a positive impact on learning (Q4)	6.0	1.1
The teacher will support the students directly if the analysis of the students' learning data reveals that they may be having some difficulty (obligation to act) (Q8)	6.4	0.9
The services associated with the use of educational data will show a comparison between the students' progress in their learning and the learning objectives or the progress of their classmates (target of intervention) (Q9)	5.5	1.3
The analysis of educational data will help me understand the learning process of the students (understanding learning) (Q10)	6.3	0.9
Perceived ease-of-use (effort expectancy)		
I believe that my knowledge is insufficient for the utilization of LA (data literacy) (Q12)	4.2	1.4
The school will provide me with guidance on how to access LA about my students (guidance) (Q13)	5.1	1.6
The school will facilitate discussions in which experiences related to the use of educational data can be shared (shared experience) (Q14)	6.2	1.0
It is necessary to train teachers on the use of LA (professional development) (Q15)	6.4	1.0

Table 3. Survey Results: Qualitative Themes

Theme	Freq. (n=73)
Question 11 (performance expectancy): How can learning data improve my understanding of my teaching practices?	
Monitoring and on-time feedback	14
Differentiated teaching	10
Teaching adaptation	8
Performance	6
Participation - engagement	5
Question 16 (concerns/anxiety): Problems-barriers that exist when using LA.	
No obstacles	24
Privacy	21
Algorithmic bias	15
Data literacy skills	7
Anxiety – stress	5
Question 17 (needs for future use): Needs required to leverage LA.	
Training	37
Technological resources	8
Communication	7
Pedagogical tools	6
Ethical issues	6
Question 21 (actionable data & actual usage): What types of learning data would benefit you in improving students' educational experiences?	
Participation - engagement	25
Understanding of learning techniques	17
Assessment	16
Time management	10
Satisfaction	5
Question 22 (intentions for future use): Do you have any suggestions for adopting LA at school?	
Hands-on training	25
Human-centered data culture	21
Easy-to-use LA tools	9
LA-based didactic scenarios	6

Facilitating conditions	Training, discussions. Technical infrastructure	I do not feel ready. I need training (T31).
Human-centeredness	Surveillance, paternalism Data privacy, CoP	What data types do we capture for LA to make sense (T32)? It would be helpful if I could configure LA based on my preferences (T36).
Data culture	Culture change	LA is out of school culture (T47).
	Informatics teachers (N=10) – Focus group 6	
Performance expectancy	Understanding learning, prediction of performance Time management. Teacher's self-evaluation Adaptation and learning design	LA saves time by focusing on more sophisticated educational activities (T52). Comparative data with other regions may disorient me. This year, I teach students with low performance. LA could awaken them (T54). Can we and do we want to make learning performance predictions? (T56)
Effort expectancy	Time and work overload	Implementing LA may take time, but I will be ready in the next few years (T55). After covid era, students and teachers don't use LMSs consistently, so we have no data to analyze (T56).
Feelings	Stress, agony Discouragement in special education	In special education, where I work, LA would stress and discourage children and parents (T57). Too many metrics with no impact could be tiring for teachers and students (T52).
Future use intentions	Guidance	What scares us is that we "first buy the car and then get the driver's license" (T53). Some teachers used LA in the COVID era, but then not (T51).
Facilitating conditions	Training, leadership	I would like an LA dashboard to monitor the learning path (T51).
Data culture	LA sense-making ICT culture	LA does not analyze many critical factors, such as the social environment (T53). Schools must adopt an ICT culture and then a data culture (T56).
	Managers (N=8) – Focus group 7	
Performance expectancy	Self-evaluation Formative assessment, differentiated teaching Motivation, help-seeking Communication. Timely alerts	Using LA, teachers can evaluate the effectiveness of teaching interventions and instructional design (M61). LA value is to see vertical sections in depth and find things that are not visible at first glance (e.g., motivation, skills) (M64). To identify mediating variables, i.e., misconceptions in education. Distribution of student absences during the school year (M63). We are extracting hidden findings using LA (M62).
Effort expectancy	Workload, time constraints, complexity Scaffolding, data cleaning and accuracy	Adults have a hard time changing attitudes (M62). The workload is worth it if implemented correctly (M64). I had misconceptions about what LA is (M62). Keep it easy-to-use. LA is an excellent technique if performed correctly; otherwise, it wastes time (M63).
Self-efficacy	Data competence. Teacher collaboration	We need ready-to-share LA-based scenarios (M65). We need to know what data is useful and how teachers use it to make decisions (M68).
Feelings	Stress, irritation. Pride	By adopting LA, I feel like a researcher adding meaning to my work. I am able, try, and succeed (M62).
Future use intentions	Hesitation Sense-making. Academic analytics	It is a lot of work but worth it (M62). In the COVID era, I used simple LA, and it mattered. I continued afterward, and it had the same positive impact (M64).

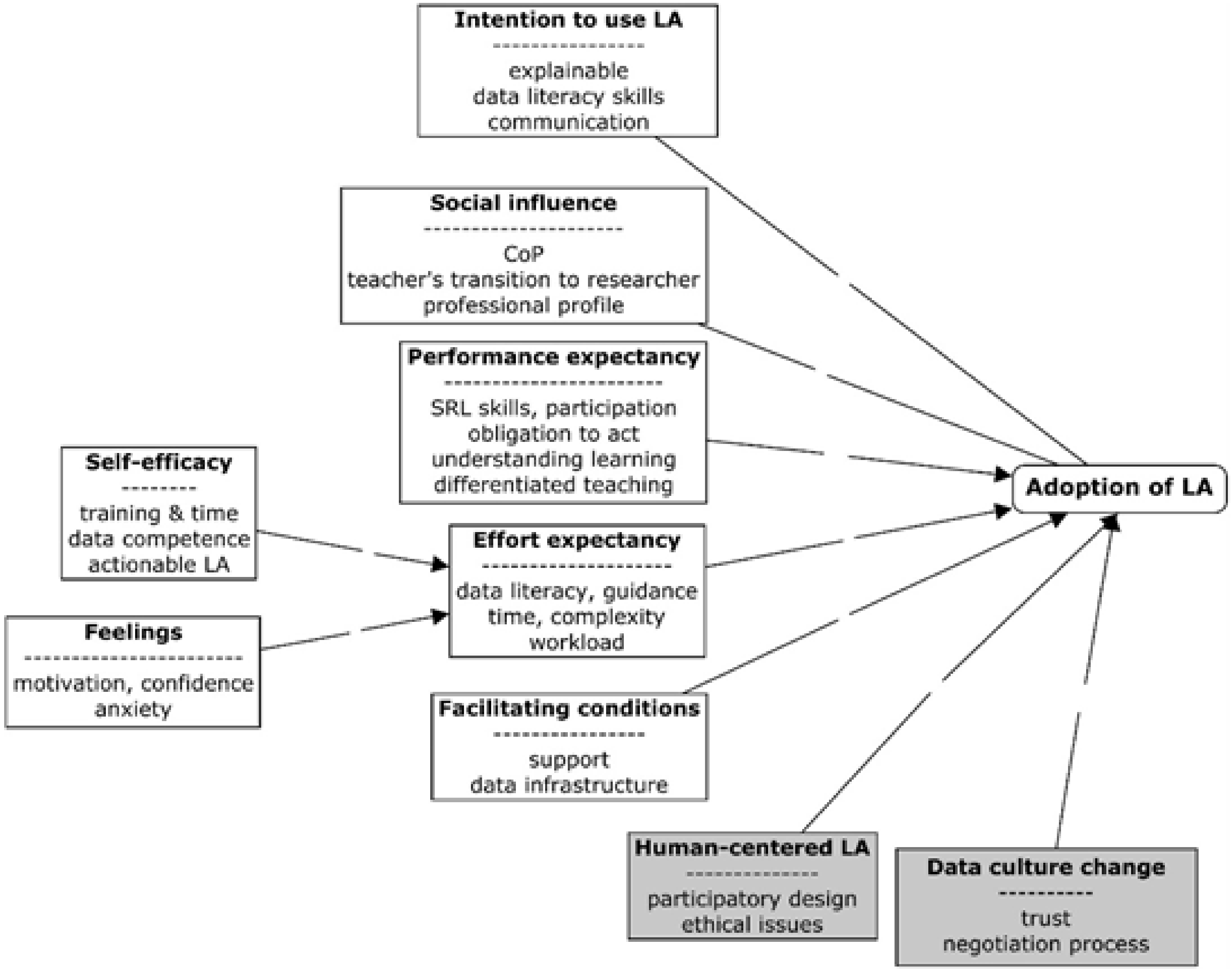


Figure 1. Classification model for adopting LA

Conclusions – Future Work

- LA advancements highlight a high tension between data mining (analytical component) and pedagogy (learning part).

- **HCAI** & HCLA

- Negotiation process

- K-12 teachers' and students' acceptance and resistance attitudes toward the adoption and implementation of learning analytics: a multi-sited **ethnographic** study.

References

- Papers in Journals

Tzimas, D., Demetriadis, S. Impact of Learning Analytics Guidance on Student Self-Regulated Learning Skills, Performance, and Satisfaction: A Mixed Methods Study. Education Sciences. **2024**; 14(1):92. https://doi.org/10.3390/educsci14010092 (IF 3.0).

Tzimas, D., Demetriadis, S. Ethical issues in learning analytics: a review of the field. Educational Technology Research and Development 69, 1101–1133 (**2021**). https://doi.org/10.1007/s11423-021-09977-4 (IF 5.4).

Tzimas, D., Demetriadis, S. K-12 Teachers' Acceptance and Resistance Perceptions of Learning Analytics Adoption: A Mixed Methods Approach (*under review* in Journal of Learning Analytics).

Tzimas, D., Demetriadis, S. K-12 teachers' acceptance and resistance attitudes toward the adoption and implementation of learning analytics: an ethnographic study (*under preparation*).

- Papers in Conferences

Tzimas, D., & Demetriadis, S. Students' Perceptions of Adopting Learning Analytics. Intelligent *Tutoring Systems: 20th International Conference, ITS **2024**,* Thessaloniki, Greece.

Tzimas, D., & Demetriadis, S. Culture of Ethics in Adopting Learning Analytics. In Augmented Intelligence and Intelligent Tutoring Systems: 19th International Conference, ITS **2023**, Corfu, Greece, June 2–5, 2023, Proceedings. Springer-Verlag, Berlin, Heidelberg, 591–603. https://doi.org/10.1007/978-3-031-32883-1_52.

Tzimas, D., & Demetriadis, S. A Literature Review of Experimental Studies in Learning Analytics. 13th Panhellenic and International Conference "ICT in Education", **2023**.

Tzimas, D., & Demetriadis, S. The Impact of Learning Analytics on Student Performance and Satisfaction in a Higher Education Course, *Educational Data Mining* (**2021**) https://bit.ly/3lwVZTo

Discussion & Take away

- We argue that change agency comes from **stakeholders** and *not through the technologies* themselves, and that **sensemaking**, how people ascribe meaning to experiences, plays a significant role in data use and technologies.

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Thank you!

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