Code of Practice for Sensor-Based Learning

Haeseon Yun[1], Shirin Riazy[2], Albrecht Fortenbacher[3] and Katharina Simbeck[4]

Abstract: Sensor-based learning refers to utilizing physiological sensor data from learners and information from a learning environment to promote learning. Sensor data enclose learner's personal information so ethical practice of adopting sensor data in learning analytics needs to be explored thoroughly. In this positional paper, we examine current ethical practices in learning analytics to derive a code of practice for sensor-based learning. Furthermore, we critically validate a wearable sensor device developed as a learning support against the derived code of practice.

Keywords: Learning Analytics, Sensor based learning, ELSI, GDPR, Sensor Data

1 Introduction and Motivation

The introduction of "General Data Protection Regulation (GDPR)" leads to an overall raised awareness of sensible data being collected and processed. Not only organizations like enterprises or universities are affected, but also individual users are prompted to consent for their data being transferred and utilized.

In order to understand learning conditions for instructors and students and to provide learners with the most appropriate context-aware feedback, learning analytics uses digital footprints in a learning environment. Even though the intention of learning analytics is noble, it is important to investigate the available measures and framework which ensure the proper usage of data. In the case of sensor-based learning support, where physiological data is used, GDPR provides an overall guideline of data privacy to protect the freedom and the rights of a person. Specifically, it should be prohibited to use any genetic or physiological data which can identify a person or can be tracked back to a user. Furthermore, any analysis and prediction of "personal aspects" to create a "personal profile" is banned [EP16]. In addition to general ethical guidelines such as the Nuremberg Code [Sh97] or the Declaration of Helsinki [As01], various researchers introduced principles [SP13], frameworks [Wi14] and checklists [DG16] in the context of learning analytics. Recently, there have also been concerns on how to deal with data-driven interventions, generated by machine learning and big data algorithms [Wi14].

Under the three-year project LISA [5] we have researched the feasibility and the implementation of sensors in a learning support system using machine learning

[1] University of Applied Science, Wilhelminenhofstraße 75A, 12459 Berlin, Germany, yun@htw-berlin.de
[2] University of Applied Science, Wilhelminenhofstraße 75A, 12459 Berlin, Germany, riazy@htw-berlin.de
[3] University of Applied Science, Wilhelminenhofstraße 75A, 12459 Berlin, Germany, forte@htw-berlin.de
[4] University of Applied Science, Wilhelminenhofstraße 75A, 12459 Berlin, Germany, simbeck@htw-berlin.de
[5] http://tel.f4.htw-berlin.de/lisa, funded by German Ministry of Education and Research, 16SV7534K

doi:10.18420/delfi2019_326

algorithms. Among various research aims, ELSI (ethical, legal, and social implications) was one major objective of the LISA project when collecting and utilizing students' data including sensor data.

In complex systems, where learner's biographical, behavioral and physiological data are used, serious and adamant reviews and critiques are necessary. Therefore, in this positional paper, we have 1) reviewed previous related research in data privacy, legal, ethical and social issues in learning analytics, 2) derived and discussed the core code of practice for sensor-based learning support and 3) critically reviewed the case of a sensor-based learning support system using the derived code of practice.

2 Derived Core Code of Practice

Based on our literature review of ethical guidelines, frameworks, principles and future considerations in the context of learning analytics, we derived six codes of practice, which are summarized in Tab. 1.

Code of Practice	**Brief Explanation**	**Reference**
Consent & Transparency	Consent of subjects (learners and teachers) and transparency of measurements and processes are required.	[SP13, Sh97, As01, Fe16, SB15, SB14, DG16, WM15, PS17, EP16]
Data Ownership	Student should act as an active agent. Data ownership, security of data storage and management should be clear.	[Fe16, Wi14, PS17, SP13, SB14, SB15, Si13, Li16, DG16, As01]
Algorithm & Interventions	Interventions should aim at positive learning. Researchers should be conscious of the purpose and effects of interventions. Algorithmic results should not be perceived as a ground truth.	[Wi14, EP16, SB15, SB14, SP13, PS17, Wi16]
Privacy	Privacy of all subjects should be protected by involving all stakeholders continuously.	[Fe16, SB15, DG16, Si13]
Legal Responsibility	Researchers should be aware of legal conduct and responsibilities. Data used for learning analytics should be accurate and up-to-date.	[SP13, Fe16, SB15, SB14, As01, DG16, Sc16]
Higher Standards	Avoid any mental and physical harm. Humanitarian benefits should play a central role. Higher ethical standards should be applied.	[Fe16, Sh97, As01, SP13, SB15, SB14, DG16, PS17]

Tab. 1: Overview of Code of Practice points for ethical research grouped by topic.

2.1 Consent & Transparency and Data Ownership

The first code of practice, consent and transparency, refers to making the usage of data by institutions clear. This includes specifying the objectives and purposes of the scope and context where data is used including collection, analysis and utilization [SB15, SB14, DG16, SP13, WM15]. When personal intervention is required, this practice implies requiring students' voluntary consent [As01, DG16, WM15]. However, as indicated by GDPR [EP16], institutes should not rely only on user's consent when processing users' data. Instead, they should consider other issues that might infringe user's rights.

Under the code of practice "data ownership", the handling of the data should engage students as "active agents" and as "collaborators" in the implementation, interventions and services of learning analytics [SP13, SB14]. In practice, this should be realized using Engelfriet's three steps ("easy access" to collected data, "the right to correct wrong information and interpretations" and "the right to remove irrelevant data") [SP13]. Additionally, it is crucial that students, as actors in learning analytics, are able to opt out from data processing [DG16, PS17, As01]. For sensor data, there have been attempts to enable transparent and integrative data handling, such as in the RECOLA Database[6] and MyData Button [Li16]. However, challenges still remain when attaining students' consent, as various reasons and factors could affect the decisions of students [PS17].

2.2 Algorithms & Interventions

To provide positive interventions, models and algorithms being used should be "sound and free from bias" ([SB14, SB15]). Specifically, Prinsloo and Slade emphasized the special care when applying artificial intelligence on educational data as "they can perpetuate, exacerbate, or mask harmful discrimination" [PS17]. To mitigate the negative effects of algorithm applied in educational data, the usage of algorithms should consider "how algorithms reinforce, maintain, even reshape visions of the social world, knowledge and encounters with information" as the application of learning analytics on educational data would "evaluate and manage corporeal, emotional and embrained lives" [Wi16, PS17]. For learning analytics interventions, one should consider that evaluations of sensor data could be biased by specific health conditions, race or gender. Student's identity and performance should be regarded as "temporal dynamic constructs" [SP13]. Various authors stated that learning analytics only provides a facet of students' behavior, therefore students' success should not be defined by the results of learning analytics but regarded as "a complex multidimensional phenomenon" [SP13, SB15, SB14]. Accordingly, it must be considered that sensor data reflects students' physiology during a comparably short time period of measurement and thus provides just a glimpse into emotional learning states.

[6] https://diuf.unifr.ch/main/diva/recola/index.html

2.3 Privacy and Legal Responsibility

[SB15] emphasized privacy as a distinctive area to consider when using learning analytics. Specifically, [DG16] proposed to 1) anonymize individual data so that they are not retrievable or trackable, 2) monitor and secure technical implementation to meet the privacy standard, 3) involve all stakeholders to secure the strict privacy measures and to be open to privacy concerns which might arise.

With respect to the legal responsibility, data processing should be fair and legal and reflect a legitimate purpose [As01]. Also, the people involved in learning analytics should be prepared for any legal consequences [DG16]. To assure the legal aspects, [Sc16] proposed the need for "extensive literature review of the legal and ethical issues around learning analytics". [SB15] emphasized the responsibility of institutions to take strict measures when dealing with students' data and providing interventions. Institutions should consult with student representatives and key members on issues of "objective, design, development, roll-out and monitoring of learning analytics" [SB15]. As sensors provide personal data, the data should both be accurate and up-to-date, and should adhere to a legal responsibility of institutions [EP16].

2.4 Higher Standards

The last derived code of practice refers to ethical principles which include both robust and sovereign purpose (greater good). Various authors state that this includes an inner attitude, namely opposing any harm to the people involved, and a regard for the society [SB15, DG16]. Based on the Nuremberg Code, the process of learning analytics should "avoid unnecessary physical and mental suffering" and it should consider any reasons of negative implications [Sh97]. Similarly, [As01] state that learning analytics should not put participating learners into any situations which cause either physical or psychological harm. To summarize, the design of a sensor-based learning support should specifically respect students' values and be in their interest [SB15, DG16, FM97].

3 Case of a Learning Support System Using Sensor Data

The LISA wearable sensor device includes both physiological sensors and sensors recording environmental data to provide self-awareness of learning states. Learners wear a LISA sensor device and interact with a learning support system which acts as a learning companion. It provides information about a learner's physiological state and about the learning environment, along with some basic and more sophisticated advice on demand.

With respect to consent & transparency and data ownership, using the sensor device may indicate automatic data collection and analysis, thus providing data ownership to the

service provider. For example, the sensor device Empatica[7], which is similar to the wristband developed in LISA, is known to collect biographical data such as name, date of birth and contact details along with all physiological and technical data. On the other hand, the LISA sensor device does not ask nor require users to provide any personal data and does not assume the data ownership. Learners' data is not transferred either to associated companies or to third parties who provide additional services nationally or internationally. Regarding algorithms & interventions, the LISA learning support system aims at providing learners with self-awareness by providing cognitive and emotional support so that learners can persist in learning. Here, privacy and transparency protect the users from potentially false interventions.

The LISA system does not record any personal data, and learners cannot be tracked by connected services using sensor data, to ensure learners' privacy. Even if learners' legitimate interests are shared by the service provider, our system requires learners' agency. Additionally, the development of LISA learning support system has been and currently is applying the higher standards by involving all stakeholders, including developers, engineers, researchers, instructors in higher education, HCI experts, communication designers, but especially students who should never be overlooked.

4 Discussion and Outlook

In this positional paper, we have reviewed previous studies that propose ethical guidelines in learning analytics. By consolidating research findings, we have derived a code of practice and conceptually applied it in the context of sensor-based learning. Then, we critically reviewed how the LISA learning support system fulfills our derived code of practice. The LISA system, in its current state, realizes a few codes of practice, namely consent & transparency, data ownership and privacy as opposed to commercially available sensor-based learning services. Our initiative to address concrete ethical issues of sensor-based learning analytics is in an early stage. However, as the critical review of sensor-based learning analytics is rare, our approach to derive a code of practice for sensor-based learning analytics is novel and necessary. Our next step will include thorough comparison of other sensor based systems to improve our code of practice.

Bibliography

[As01] Association, World Medical et al.: World Medical Association Declaration of Helsinki. Ethical principles for medical research involving human subjects. Bulletin of the World Health Organization, 79(4):373, 2001.

[DG16] Drachsler, Hendrik; Greller, Wolfgang: Privacy and analytics: it's a DELICATE issue a checklist for trusted learning analytics. In: Proceedings of the sixth international conference on learning analytics & knowledge. ACM, S. 89–98, 2016.

[7] https://www.empatica.com/privacy/

[EP16] European Parliament, Council of the European Union: , DIRECTIVE (EU) 2016/680 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 27 April 2016., 2016. Online; accessed 18 March 2019.

[Fe16] Ferguson, Rebecca; Hoel, Tore; Scheffel, Maren; Drachsler, Hendrik: Guest editorial: Ethics and privacy in learning analytics. SoLAR, 2016.

[FM97] Friedman, Batya; Millet, Lynette I: Reasoning About Computers as Moral Agents: A Research Note. In (Friedman, Batya, Hrsg.): Human values and the design of computer technology, Kapitel 11, S. 201–205. Cambridge University Press, 1997.

[Li16] Ligon, Glynn D.:MyData Button: Button, Button, Who's Got the Button? Nobody! Click one button and get all your education data! Too good to be true? Yes., 2016. Online; accessed 16 March 2019.

[PS17] Prinsloo, Paul; Slade, Sharon: Ethics and learning analytics: Charting the (un) charted. SOLAR, 2017.

[SB14] Slade, S; Boroowa, A: Policy on ethical use of student data for learning analytics. Milton Keynes: Open University UK, 2014.

[SB15] Sclater, Niall; Bailey, Paul: Code of practice for learning analytics. 2015.

[Sc16] Sclater, Niall: Developing a Code of Practice for Learning Analytics. Journal of Learning Analytics, 3(1):16–42, 2016.

[Sh97] Shuster, Evelyne: Fifty years later: the significance of the Nuremberg Code. New England Journal of Medicine, 337(20):1436–1440, 1997.

[Si13] Siemens, George: Learning analytics: The emergence of a discipline. American Behavioral Scientist, 57(10):1380–1400, 2013.

[SP13] Slade, Sharon; Prinsloo, Paul: Learning analytics: Ethical issues and dilemmas. American Behavioral Scientist, 57(10):1510–1529, 2013.

[Wi14] Willis, JE: Learning analytics and ethics: A framework beyond utilitarianism. Educause Review, 2014.

[Wi16] Williamson, Ben: Coding the biodigital child: the biopolitics and pedagogic strategies of educational data science. Pedagogy, Culture & Society, 24(3):401–416, 2016.

[WM15] Welsh, Simon; McKinney, Stewart: Clearing the fog: A learning analytics code of practice. 2015.