Designing Feedback for Collocated Teams using Multimodal Learning Analytics

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Certificate of Original Authorship

I, Vanessa Echeverria Barzola, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Connected Intelligence Centre at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Preface and Notes

The following peer-reviewed publications produced during the PhD candidature contribute to this thesis.

Journal Papers

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- **Vanessa Echeverria,** Roberto Martinez-Maldonado, Simon Buckingham Shum, Katherine Chiluiza, Roger Granda, Cristina Conati (2018). Exploratory versus Explanatory Visual Learning Analytics: Driving Teachers' Attention through Educational Data Storytelling. Journal of Learning Analytics, 5(3), (pp. 72-97).

Conference Proceedings

- Roberto Martinez-Maldonado, **Vanessa Echeverria**, Gloria Fernandez Nieto, Simon Buckingham Shum (2020). From Data to Insights: A Layered Storytelling Approach for Multimodal Learning Analytics. Accepted for the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20).

- Simon Buckingham Shum, **Vanessa Echeverria**, Roberto Martinez-Maldonado (2019). The Multimodal Matrix as a Quantitative Ethnography Methodology. In International Conference on Quantitative Ethnography (pp. 26-40). Springer, Cham.

- **Vanessa Echeverria**, Roberto Martinez-Maldonado, Simon Buckingham Shum (2019). Towards Collaboration Translucence: Giving Meaning to Multimodal Group Data. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19), Paper 39, 16 pages, ACM, New York, NY, USA.

- Roberto Martinez-Maldonado, **Vanessa Echeverria**, Doug Elliott, Carmen Axisa, Tamara Power, Simon Buckingham Shum (2019). Making the Design of CSCL Analytics Interfaces a Co-design Process: the Case of Multimodal Teamwork in Healthcare. In Proceedings of the 13th International Conference on Computer Supported Collaborative Learning (CSCL) 2019, Volume 2 (pp. 859-860). Lyon, France: International Society of the Learning Sciences.

- **Vanessa Echeverria**, Roberto Martinez-Maldonado, Tamara Power, Carolyn Hayes, Simon Buckingham Shum (2018). Where is the nurse? towards automatically visualising meaningful team movement in healthcare education. In International conference on

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- **Vanessa Echeverria**, Roberto Martinez-Maldonado, Simon Buckingham Shum (2017). Towards data storytelling to support teaching and learning. In Proceedings of the 29th Australian Conference on Computer-Human Interaction (OZCHI '17). ACM, New York, NY, USA, (pp. 347-351).
- **Vanessa Echeverria**, Roberto Martinez-Maldonado, Katherine Chiluiza, S Buckingham Shum (2017). DBCollab: Automated feedback for face-to-face group database design. In Proceedings of the 25th International Conference on Computers in Education, ICCE 2017-Main Conference Proceedings. (pp. 156 - 165).

Workshop Papers

- Roberto Martinez-Maldonado, **Vanessa Echeverria**, Kalina Yacef, Augusto Dias Pereira Dos Santos, Mykola Pechenizkiy (2017). How to capitalise on mobility, proximity and motion analytics to support formal and informal education?. In MMLA- CrossLAK 2017 (pp. 39-46). (CEUR Workshop Proceedings; Vol. 1828). CEUR-WS.org.

Workshops

- Roberto Martinez-Maldonado, **Vanessa Echeverria**, Luis P Prieto, Maria Jesus Rodriguez-Triana, Daniel Spikol, Mutlu Curukova, Manolis Mavrikis, Xavier Ochoa, Marcelo Worsley (2018). 2nd CrossMMLA: Multimodal learning analytics across physical and digital spaces. In MMLA- CrossLAK 2018. (CEUR Workshop Proceedings; Vol. 2163). CEUR-WS.org.

Sources and Original Work

Original material of my own from the above publications has been included in this thesis. Such prior publications when used in the thesis are explicitly cited where appropriate and are not used in entirety. Publications of external authors are credited throughout the thesis with citations in text and references at the end of the thesis. Figures from external sources where authors granted permission for usage are cited in their captions.

Ethics

The studies presented in this thesis were conducted under ethics approved by the University of Technology Sydney's Human Research Ethics Committee, and are based on projects ETH17-1411: Learning Analytics for understanding small-group collaborative processes; ETH17-1415: Measuring Adoption and Acceptance of Learning Analytics Tools and ETH17-1502: Learning Analytics in clinical simulation. A revised version of the ethics project ETH17-1502 has the protocol number ETH18-2278. The most recent participant information sheets and consent forms can be requested by email[1].

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List of Abbreviations

LA	Learning Analytics
MMLA	Multimodal Learning Analytics
HCI	Human Computer Interaction
HCD	Human-Centred Design
CSCL	Computer-Supported Collaborative Learning
CSCW	Computer-Supported Collaborative Work
DS	Data Storytelling
InfoVis	Information Visualisation
QE	Quantitative Ethnography
TUI	Tangible User Interfaces
DBR	Design Based Research
IPA	Interaction Process Analysis
ACAD	Activity-centred Analysis and Design
CPS	Collaborative problem solving
EDA	Electrodermal Activity
HCD-MMLA	Human-Centred Design Multimodal Learning Analytics
HoC	Higher order constructs
OV	Original visualisations
VDS	Visualisations with data storytelling elements
EvisLA	Explanatory Visual Learning Analytics

Abstract

The ability to communicate, be an effective team or group member and collaborate face-to-face are critical skills for employability in the 21st century workplace. Previous research suggests that learning to collaborate effectively requires practice, awareness of group dynamics and reflection upon past activities. However, although having a teacher closely supervising and providing detailed feedback to each group would be ideal, it may be unrealistic in practice. A promising way to approach this challenge could be to capture behavioural traces from group interactions in order to generate comprehensible and actionable feedback to support team reflection. In this sense, Multimodal Learning Analytics (MMLA) is a promising field, offering the potential to track learners' activity across digital and collocated contexts, using emerging sensing and pervasive computing technologies. Most of the research in MMLA has been conducted in lab conditions, to help researchers validate learning theories or generate more comprehensive learner models. However, one of the most underexplored aspects of MMLA has been the generation of feedback to support teaching and learning, and moreover, in authentic locations and activities.

This thesis reports progress in tackling this challenge by designing and validating computer-based feedback, by means of visual representations and narrative, to support effective, guided reflection using multimodal learning analytics evidence. To achieve this, three contributions are presented. The first contribution is a human-centred design method to translate the informal outputs of co-design sessions with teachers and students, into more meaningful group work constructs with clear MMLA design requirements. The second contribution is a modelling approach to add meaning to low-level multimodal group data based on the characteristics of the context (domain expertise, theory, and the learning design). Finally, the third contribution is an approach for augmenting visual representations with data storytelling elements to facilitate the interpretation of group dynamics insights by educators and students. This thesis is developed in the context of two distinct, collocated group work settings, in the domains of collaborative database design and healthcare simulation. Using a Design-Based Research process, a set of *explanatory* interfaces (i.e. interfaces that communicate insights) was designed and validated with teachers and students. The thesis provides timely and necessary groundwork for researchers and practitioners to design visual representations capable of communicating actionable insights, using multimodal data in complex and authentic collaboration scenarios.