Modelling Engagement in Technology-mediated Peer-Instruction

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ABSTRACT

TO DO

CCS CONCEPTS

• **Applied computing → Computer-assisted instruction**; • **Computing methodologies → Natural language processing**.

KEYWORDS

Peer Instruction, Learnersourcing

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1 INTRODUCTION

Technology-mediated peer instruction *(TMPI)* platforms [1][8] expand multiple choice items into a two step process. On the first step, students must not only choose an answer choice, but also provide an explanation that justifies their reasoning. On the second step, students are prompted to revise their answer choice, by taking into consideration a subset of explanations written by their peers for another answer choice. In the case that the student wants to keep their original answer choice, but may be unsure of their own explanation, they are also shown peer-explanations for their own same answer choice. The student now has three options:

(1) Change their answer choice, by indicating which of their peer's explanations was most convincing
(2) keep their answer choice, but *change explanations* by choosing one that is for the same answer as their own
(3) choose "I stick to my own", indicating that their own explanation is best from amongst those that are shown.

The design of TMPI is inspired by three schools of thought: firstly, prompting students to explain their reasoning is beneficial to their learning [3]. Second, classroom based *Peer Instruction*[4], often mediated by automated response systems (e.g. clickers), has become a prevalent, and often effective component in the teaching practice of instructors looking to drive student engagement as part of an active learning experience [2]. In discussing with peers *after* they have formulated their own reasoning, students are engaged with a higher order thinking task from Bloom's taxonomy as the evaluate what is the strongest argument, before answering again. Thirdly, by capturing data on which explanations students find most convincing, TMPI affords teachers the opportunity to mitigate the "expert blind spot" [5], addressing student misconceptions they might not otherwise have known of.

In many teaching contexts, however, teachers do not have the time to review, and provide feedback, to every student explanation for every question item. The feedback students receive is primarily based on the correctness of their first and second answer, not the explanations they write and choose. Moreover, activities from online learning environments are often used for formative assessment, and carry little weight in terms of course credit. Framed as a low-stakes test, this can lead to low student motivation [10]. A version of the expectancy-value model [6], which describes factors that influence the effort students will direct towards a task, includes "how important they perceive the test to be", and the "affective reaction to how mentally taxing the task appears to be" [11].

This may explain, in part, the tendency for students to simply "stick to their own", as shown in figure 1. Of the students who choose the correct answer choice on the first step, more than half choose their own as "most convincing" over the explanations that are shown on the *review* step (39% vs 35%). Of those who begin with incorrect answer, and maintain their incorrect answer on the review step, we find approximately the same relative ratios (9% vs 8%). The last third of these students demonstrate some form of *learning* as well, as they transition to the correct answer after reading their peer's explanations.

In this work, we suggest that if we can accurately model when students *change* explanations, we may have proxy for student *engagement.* Being able to identify when students are likely to be "disengaged" in their formative assessment activities can serve as valuable information for instructors, as well as the designers of TMPI learning environments.

We also explore the utility of "learnersourced" data in our models of student engagement. Each time an explanation is chosen as most convincing by a student, it earns a"vote". These votes represent a proxy for argument quality along the dimension of *convincingness*,

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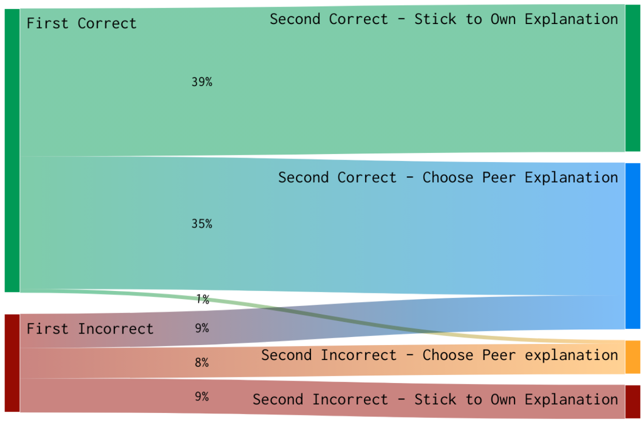

Figure 1: Sankey Diagram depicting transitions in peer-instruction platform. On the left, responses are separated by whether the student chose the correct answer at the first step, or not. For each of these two scenarios, there are three possible transitions towards the right: a) keep the same answer choice, and choose their own explanation, b) keep the same answer choice, and choose a peer's explanation, or c) choose a different answer choice (by choosing a peer's explanation for the other answer choice option presented) TO DO: make diagram for different disciplines

as judged by peer learners. We set out to examine the relationship between the *convincingness* of student explanations, and their *engagement* in the learning activity.

2 RELATED WORK

This modality is a specific case of *learnersourcing*[9], wherein students first generate content as part of their own learning process, that is ultimately used to help their peers learn as well.

2.1 Engagement

2.2 Modelling Argument Persuasiveness

3 METHODOLOGY

3.1 Engagement

$$Engagement_{student} = \overline{P(ChosenExplanation \neq OwnExplanation)} \tag{1}$$

3.2 Features

3.2.1 Surface Features.

(1) Word count of explanation that the student wrote
(2) Word counts of explanations that were shown on the review step
(3) Number of explanations shown that were much shorter, or much longer than than the student's own explanation
(4) First answer correct

3.2.2 Convincingness Features. Two measures of *convincingness* are explored in this work:

(1) **Win Rate**: a heuristic measure [7]
(2) **Bradley-Terry**

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TO DO

REFERENCES

[1] Elizabeth S. Charles, Nathaniel Lasry, Sameer Bhatnagar, Rhys Adams, Kevin Lenton, Yann Brouillette, Michael Dugdale, Chris Whittaker, and Phoebe Jackson. 2019. Harnessing peer instruction in- and out- of class with myDALITE. In *Fifteenth Conference on Education and Training in Optics and Photonics: ETOP 2019*. Optical Society of America, 11143_89. http://www.osapublishing.org/abstract.cfm?URI=ETOP-2019-11143_89
[2] Elizabeth S. Charles, Nathaniel Lasry, Chris Whittaker, Michael Dugdale, Kevin Lenton, Sameer Bhatnagar, and Jonathan Guillemette. 2015. Beyond and Within Classroom Walls: Designing Principled Pedagogical Tools for Student and Faculty Uptake. International Society of the Learning Sciences, Inc.[ISLS].
[3] Michelene TH Chi, Nicholas Leeuw, Mei-Hung Chiu, and Christian LaVancher. 1994. Eliciting self-explanations improves understanding. *Cognitive science* 18, 3 (1994), 439–477.
[4] Catherine H Crouch and Eric Mazur. 2001. Peer instruction: Ten years of experience and results. *American Journal of Physics* 69, 9 (2001), 970–977.
[5] Mitchell J Nathan, Kenneth R Koedinger, Martha W Alibali, and others. 2001. Expert blind spot: When content knowledge eclipses pedagogical content knowledge. In *Proceedings of the third international conference on cognitive science*, Vol. 644648.
[6] Paul R Pintrich. 1989. The dynamic interplay of student motivation and cognition in the college classroom. *Advances in motivation and achievement* 6 (1989), 117–160.
[7] Peter Potash, Adam Ferguson, and Timothy J Hazen. 2019. Ranking passages for argument convincingness. In *Proceedings of the 6th Workshop on Argument Mining*. 146–155.
[8] Teaching & Learning Technologies Univeristy of British Columbia. 2019. ubc/ubcpi. https://github.com/ubc/ubcpi original-date: 2015-02-17T21:37:02Z.
[9] Sarah Weir, Juho Kim, Krzysztof Z Gajos, and Robert C Miller. 2015. Learnersourcing subgoal labels for how-to videos. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*. ACM, 405–416.
[10] Steven L Wise and Christine E DeMars. 2005. Low examinee effort in low-stakes assessment: Problems and potential solutions. *Educational assessment* 10, 1 (2005), 1–17. Publisher: Taylor & Francis.
[11] Lisa F Wolf, Jeffrey K Smith, and Marilyn E Birnbaum. 1995. Consequence of performance, test, motivation, and mentally taxing items. *Applied Measurement in Education* 8, 4 (1995), 341–351. Publisher: Taylor & Francis.