Modelling Argument Quality 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

ACM Reference Format:
Sameer Bhatnagar, Antoine Lefebvre-Brossard, Michel C. Desmarais, and Amal Zouaq. 2021. Modelling Argument Quality in Technology-Mediated Peer-Instruction. In *Proceedings of LAK '21: Learning Analytics & Knowledge (LAK '21).* ACM, New York, NY, USA, 2 pages. https://doi.org/10.000/0000.0000

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 original 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.

LAK '21, April 2021, UCI,CA

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.000/0000.0000

Whenever the student goes with either of the first two scenarios above, we frame this as "casting a vote" for the chosen peer explanation.

The design and growing popularity 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 in a higher order thinking task from Bloom's taxonomy, as they 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 thought of.

In many teaching contexts, however, teachers do not have the time to 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 choices, 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]. 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 makes providing feedback to students on the quality of their explanations a desirable goal, in order to emphasize the importance of the writing activity, as well as promote engagement. The data at hand in TMPI environments enable scaling up how much feedback that can given. The "vote" data represent a proxy for argument quality along the dimension of *convincingness*, as judged by peer learners. These votes can be aggregated into a *convincingness* score to students, as a measure of how effective their explanations are in persuading their peers to change their own answer.

We set out to examine the different measures of argument quality, along the dimension of *convincingness*, and model their role in the TMPI process. Our specific research questions are:

RQ1 What factors influence whether a student will choose a peer's explanation over their own in TMPI?

RQ2 What measures of argument *convincingness* are most useful in aggregating the "vote" data from TMPI?

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**

ACKNOWLEDGMENTS

TO DO

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