Using Practical Measures to Predict Computing Outcomes

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ABSTRACT

Measures typically used in computing education research at the elementary-school level that are aimed at measuring student learning outcomes are not capable of identifying instructional practices that contribute to improvements in learning. On the other hand, practical measures that help practitioners prioritize efforts aimed at improvement in instructional practices are limited in their capability to predict student learning outcomes. Thus, in this research, a combination of these practical and summative measures will be used to study complex interplays between students' perceptions, motivations, and final learning outcomes. For analysis, latent growth curve modeling will be used on student experience exit ticket data to measure the change in students' perceptions of the instructional intervention over lessons. Using the structural equation modeling approach, the latent growth model shall also incorporate a predictive relationship between the student experience exit ticket responses to the changes in the outcome measures from the pre and post surveys. Preliminary work on the working theory has been done that explains a theoretical relationship between practical measures and outcome measures, explaining how outcomes will be produced and how practical measures can help predict certain outcomes.

CCS CONCEPTS

• **Social and professional topics** → Professional topics; Computing education; Student assessment.

KEYWORDS

Improvement Science, Practical Measures, Learning Outcomes

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1 MOTIVATION

Much of the research in formal computing education at the elementary-school level is focused on finding new and improved ways to teach computing. However, the measures typically used in the said literature are focused on measuring cognitive or behavioral constructs e.g., [9, 11, 13], designed to inform research. In the field of computing education, there is a constant need for finding ways to use data in a way that informs instructional practices and decisions that educators and instructional designers have to make. Measures that are aimed at informing practice are called practical measures; they help practitioners prioritize efforts aimed at improving instruction [16]. These measures are designed to be less time-and-effort-intensive to administer, hence they can be conducted more frequently. However, since the foremost purpose of these measurements is informing practice, there is a tradeoff, i.e., practical measures are not designed to measure outcomes. Researchers are thus faced with the decision of choosing between the precision and practicality of a measure [1]. Since practical measures and outcome measures have their own distinct set of advantages and disadvantages, using them together can offer a unique set of advantages (see Table 1).

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2 BACKGROUND

2.1 Research Context

As part of a larger project, a research team is collaboratively-designing (co-designing) instructional units with a local school district for a grade 5 curriculum in which math and CS concepts are integrated. In a subset of these schools, co-designed adaptations for standards-based mathematics curriculum are also taught in which CS concepts are integrated into regular math lessons. This builds connections between math and CS, helping students learn CS and math across the two learning settings. As part of this project, different forms of measures are being administered to students. Short student experience exit tickets to capture student experience will be administered after each integrated lesson. Pre and post surveys will be administered to collect student affective and assessment data to evaluate student learning of computing concepts.

2.2 Literature Review

Student experience exit tickets are short-format surveys the teachers can administer [10] at the end of each unit of instructional intervention, and are used to inform educators' instructional practices [12]. These are repeated to inform recurring practices [12] and can be used to predict important outcomes [16].

Existing CS literature has identified an extant set of constructs that can be categorized as outcome variables. Examples include self-efficacy, interest, content knowledge, computational thinking, utility value, persistence etc. Practical as well as outcome measures should inform prioritizing instructional practice and design efforts.

Based on literature review, Figure 1 distills relationships between different measures used in the context of computing education as well as in related motivational literature. The prior research informs the selection of these measures in two ways. First, it informs what constructs are suitable as practical or outcome measures. Second, it explains the relationship between the said constructs. Both of

Table 1: A comparison of different advantages of practical measures and outcome measures.

Practical measures advantages	Outcome measures advantages
Informs practice decisions	Assesses change over time
Less time consuming to administer	More in-depth examination of learning
Geared toward improvement	Parses out influences of overlapping constructs
Can be administered frequently	Targets long-term change
Experience is measured	Users answer by reflecting on a collection of experiences

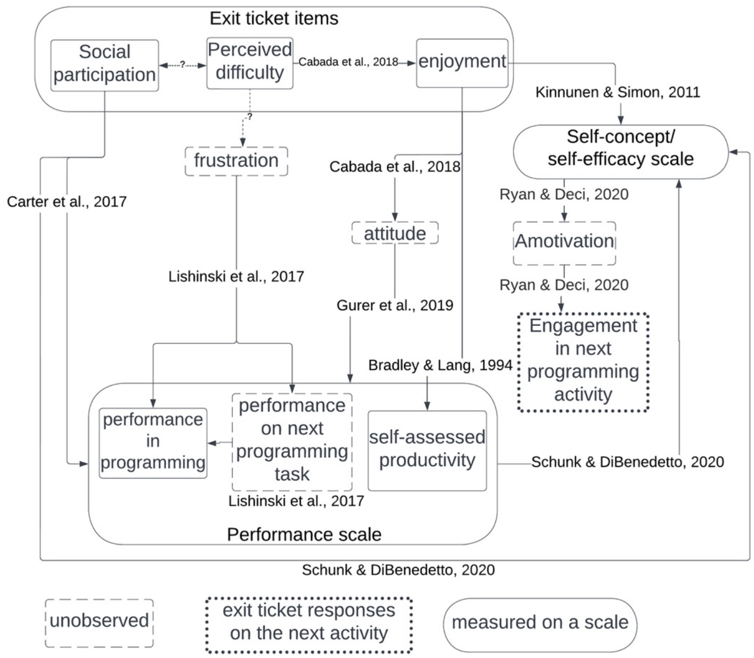

Figure 1: Relationships between exit ticket and outcome measures, as distilled for a literature review [2–5, 7, 8, 14, 15]

these considerations would affect the choice of constructs, as the goal is to produce a working theory that explains how the outcomes are produced [16]. For example, perceived ease of tasks [6], frustration [8], and being stuck on a task [6], have all been used as single-item measures, hence are suitable as practical measures. However, perceived ease/difficulty fits better within the working theory (see Figure 1) for a few different reasons. Perceived ease is a more established measure compared to the measures of frustration or the measure of being stuck on a task, as it has been studied more widely in the literature. It also translates to an exit ticket item better than the other two variables. For example, the perceived ease or perceived difficulty can be translated to a spectrum in the form of a Likert scale item; on the other hand, whether the learner was stuck on a problem is better asked as a yes/no question. Another criterion for selecting practical measures is that they should relate to underlying causes of problems [16]. Since perceived difficulty may be the underlying reason for a student's frustration with the task and the frustration predicts long-term and short-term performance [8], perceived ease/difficulty fits this criterion as well. Applying the same criteria of selecting constructs based on their strong foundations in the empirical and theoretical literature, translation to a one-item response on a Likert scale, and direct relationship to underlying causes to problems that influence outcomes; enjoyment, and social participation are also good candidates for exit ticket items.

3 RESEARCH QUESTION

This literature review leads to the following research questions examined in my dissertation study:

What practical measures (as captured in student experience exit tickets) predict student CS learning?

What outcome measures (measured using pre and post surveys) can be reliably predicted by practical measure?

4 RESEARCH APPROACH, METHODS, AND PROGRESS

The goal of analyses will be to map student experience exit ticket measures onto the outcomes measured using the long format surveys administered at the start and the end of the instructional interventions. Once a practical measure item is shown to reliably predict an outcome, it can be used in a similar setting to help practitioners predict outcomes and identify areas of improvement. This will inform practice in real-time and would give educators and instructional designers the opportunity to course-correct during the implementation, and will help them identify and set priorities that attain improved learning outcomes.

To measure the difference in exit ticket items across the lessons, a within-subject design is needed. Latent growth curve analysis will be used to measure change over lessons as it offers advantages over repeated measures ANOVA and multilevel regression. The latent factors related to change in practical measure across lessons will be used to predict outcomes measured in the form of student self-efficacy and knowledge. If a practical measurement item is able to predict an outcome, a predictive relationship will be established. This will be followed by a subsequent round of exploratory factor analysis (EFA). Based on the results of the EFA, a set of recommendations will be produced for the design of the next version of instruments that will be used in the subsequent implementation. The results of how the predictive ability of student experience exit tickets is used by the practitioners and design team will be reported in the dissertation. Through my dissertation study, I hope to contribute to CS education by improving the field's understanding of practical measures and how they can inform design and instructional practices in real-time.

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