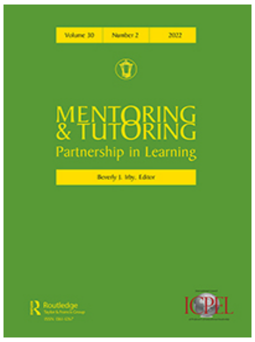

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ARTICLE

Testing the efficacy of a near-peer mentoring model for recruiting youth into computer science

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ABSTRACT

We developed a near-peer mentoring model for high school youth to mentor middle school youth on how to program using MIT App Inventor. The purpose of this study was to investigate (a) the effectiveness of the near-peer mentoring model for the mentees and (b) how the mentees' vicarious experience with the near-peer mentors led to changes in their self-efficacy in computer programming. Findings provide evidence for the effectiveness of the model in improving self-efficacy. A moderation analysis showed how mentor role modeling and perceived similarity contributed to the changes in self-efficacy. Explanations to the findings and their implications are discussed.

KEYWORDS

Self-efficacy; near-peer mentoring; similarity; modeling; vicarious experience; computer programming

Underrepresentation is still a prominent issue in computer science (CS; National Science Board, 2018; National Science Foundation [NSF], 2018). Due to the current limitations of finding instructional time for CS in K-12 public schools (Code.org, 2018; Google Inc. & Gallup Inc., 2015), many initiatives for broadening CS participation happen in informal spaces such as after-school clubs (e.g. Maloney, Peppler, Kafai, Resnick, & Rusk, 2008) and summer programs (e.g. Adams, 2007; Roy, 2012; Sabin, Deloge, Smith, & Dubow, 2017). Across these initiatives, mentoring is a common practice used to introduce youth (who we define as children between the ages of 10 and 17) to CS and has been found to be associated with positive change in youth's affect toward CS (e.g, Khoja, Wainwright, Brosing, & Barlow, 2012; Pollock, McCoy, Carberry, Hundigopal, & You, 2004; Sabin et al., 2017).

As part of the joint efforts to expand the CS pipeline, we have been running NSF-sponsored summer camps to introduce novice youth learners to programming with App Inventor, a block programming language. One of the camp's goals is to promote youth's self-efficacy and interest in CS-related activities. To that end, we developed a near-peer mentoring model in the expectation that by training high school students to be near-peer mentors, they would deliver an

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enhanced learning experience for the middle-school-aged mentees. The purpose of the present study is thus to examine the effectiveness of the mentoring model for the mentees. In particular, this study only focuses on the mentees' vicarious experience with the near-peer mentors and how it influenced the mentees' self-efficacy and interest in programming.

Near-peer mentoring model

The near-peer mentoring model was designed based on Bandura's (1977, 1997) theorization on self-efficacy and its sources. Self-efficacy is hypothesized as a primary determinant of choice of activities, effort expenditure, and persistence. Furthermore, the social cognitive career theory (Lent, Brown, & Hackett, 1994), a theory built upon social cognitive theory (Bandura, 1986), also recognizes the crucial role of self-efficacy in career development. It posits that self-efficacy affects career development via its influence on outcome expectations, interests, choice goals, and choice actions. Given its importance, the near-peer mentoring model was designed around self-efficacy in order to affect youth's interest in programming.

According to Bandura (1977, 1981, 1986, 1997), self-efficacy expectations are influenced by four sources of information: enactive experience (i.e. successes and failures), vicarious experience (i.e. observing others), verbal persuasion (i.e. encouragement or discouragement), and physiological state (i.e. fear or sweating). The near-peer mentoring model focused on the first three sources (i.e. enactive and vicarious experience, and verbal persuasion). Specifically, the model prescribed high school students as the intervention agents and utilized them as near-peer mentors to (a) improve the mentees' enactive experience and (b) enrich their vicarious experience and perceived persuasion. We hypothesized that these enhanced experiences would raise the mentees' self-efficacy in programming, which in turn would lead to heightened interest in CS and CS careers. However, for the purpose of the present study, only the mentees' vicarious experience will be examined and discussed.

Sources of self-efficacy

Vicarious experience as a source of self-efficacy

Vicarious experience can influence self-efficacy expectations through a process of social comparison to other people (i.e. models) (Bandura, 1977, 1981, 1986, 1997). In this sense, vicarious experience is an experience established in relation to the models and their attainments. By observing and comparing themselves to the models, people draw inferences on their own abilities in executing a task as the models do. In Bandura's (1997) own words, 'seeing or visualizing people similar to oneself perform successfully typically raises efficacy beliefs in observers that they themselves possess the capabilities to master comparable activities' (p. 87). There are several conditions under which efficacy appraisal is particularly sensitive to vicarious influence. In the absence of prior experience and direct knowledge of their capabilities, vicarious experience is a major source of information that people rely on to appraise their efficacy. Vicarious experience can also mitigate the sense of inefficacy derived from previous experiences and improve efficacy expectations.

Numerous researchers (e.g. Usher & Pajares, 2008; Zeldin & Pajares, 2000) have corroborated the impact of vicarious experience in fostering self-efficacy. For example, Zeldin and Pajares (2000) interviewed 15 women with STEM (science, technology, engineering, and mathematics) careers and found that vicarious experience as well as verbal persuasion was the critical sources of those women's confidence in pursuing careers in male-dominated domains. In another study, Lin (2016) surveyed 1073 Taiwanese undergraduate CS majors on their learning self-efficacy, computer self-efficacy (i.e. self-efficacy in using computers), programming self-efficacy, and sources of those self-efficacies. Regression analyses showed that vicarious experiences were the primary predictor of females' computer self-efficacy. Furthermore, in several meta-analytic and review studies on sources of self-efficacy, researchers surveyed studies conducted from the 1970s to the 2010s (e.g. Sheu et al., 2018; Usher & Pajares, 2008), in different domains such as STEM and non-STEM fields (e.g. Byars-Winston, Diestelmann, Savoy, & Hoyt, 2017), and across different gender and ethnic groups (e.g. Lent et al., 2018), and have found that vicarious experience was a significant predictor of self-efficacy.

In addition, researchers across various academic disciplines and domains such as mathematics and statistics (e.g. Huang, 2017; Schunk & Hanson, 1985; Schunk, Hanson, & Cox, 1987; Zimmerman & Ringle, 1981), science (e.g. Hoogerheide, Loyens, & van Gog, 2016; Hoogerheide, van Wermeskerken, Loyens, & van Gog, 2016; Hoogerheide, van Wermeskerken, van Nassau, & van Gog, 2017), and second language education (e.g. Murphey & Arao, 2001; Murphey & Murakami, 1998) also have suggested that interventions on vicarious experience were able to raise students' self-efficacy. Murphey and Murakami (1998), as an example, used video models as a source of vicarious influence to affect undergraduate EFL (i.e. English as a foreign language) learners' language learning beliefs. Both quantitative and qualitative findings attested to the positive effect of the intervention procedure on the students' views of English language learning. In another study using the same video, Murphey and Arao (2001) observed an immediate increase in the students' motivation after watching the video and a subsequent higher level of motivation at the end of the study. In a series of studies, Hoogerheide and colleagues (2016, 2016, Hoogerheide et al., 2017) have showed that viewing a videotaped model perform a new task (i.e. solving an electric circuit problem or a probability calculation in different studies) was effective in fostering students' self-efficacy in learning the new task.

Vicarious modeling

Modeling (a process where the behaviors, verbalizations, and expressions of a model that are attended to by an observer result in the latter's behavioral change (Schunk, 1987)) is an effective tool to promote the impact of vicarious experience on self-efficacy (Bandura, 1997). For instance, Bandura (1997) argued that modeling can reverse the negative impact of failures on self-efficacy and sustain persistence in the face of repeated failures. Bandura (1977, 1981, 1986, 1997) further hypothesized that the modeling effect on self-efficacy expectations depends on the perceived similarity to the model – the greater the similarity, the greater the vicarious influence on increasing self-efficacy. Conversely, a perceived difference from a model reduces people's sense of relevance for comparing themselves to the model. Therefore, a model with marked differences has limited power in influencing an observer's self-efficacy. As Bandura (1997) noted, '[given large perceived disparities in experiences, children are likely to view skills exemplified by an experienced model as beyond their reach and are thus declined to invest the effort needed to master them fully' (p. 234).

The model-observer similarity is framed around the model's performance abilities and personal attributes such as age and gender that are presumably predictive of capabilities (Bandura, 1977, 1981, 1986, 1997). According to Bandura (1981), models 'who are similar or slightly higher in ability provide the most informative comparative information for gauging one's own capabilities' (p. 207). As to model attributes, Bandura (1981) argued that attribute similarity can generally strengthen modeling impacts on self-efficacy. Because people use age, gender, educational and socioeconomic levels and other attribute information as cues of one's performance capabilities, the success of a model with similar attributes will imply to the observers that they also possess the abilities to succeed.

Numerous researchers have detected evidence in favor of the hypothesis on model-observer age and ability similarity, which hypothesizes that models of similar age and ability are more effective in enhancing self-efficacy than models with large age and ability differences (e.g. Baylor & Kim, 2004b; Groenendijk, Janssen, Rijlaarsdam, & van den Bergh, 2013; Huang, 2017; Schunk, 1987b; Schunk & Hanson, 1989; Schunk et al., 1987; Selzler, Rogers, Berry, & Stickland, 2020; St-Jean, Radu-Lefebvre, & Mathieu, 2018). For example, Schunk and Hanson (1985) sampled students with deficient subtraction skills and assigned them to one of the conditions: viewing the video of an adult model providing instruction to a peer student model with comparative subtraction skills to themselves and the peer model modeling subtraction operations, or the same adult model instructing alone without the peer model, or no video modeling. Results indicated that students in the peer model conditions had higher self-efficacy than those in adult and no model conditions. In a follow-up study (i.e. Study 1), Schunk et al. (1987) found that observing coping models who were more similar in math competence led to higher self-efficacy than observing mastery models with more advanced abilities. In another study, Baylor and Kim (2004) observed similar results using animated models. They created three age group agents varying by levels of expertise: much older, professor-like agents of extensive knowledge, slightly older, mentor-like agents with slightly higher expertise than the participants, and similar-aged, peer-like agents with limited knowledge. Students who worked with the younger and more peer-like agents and mentor-like agents reported higher self-efficacy than those who worked with the older, professor-like agents. In addition, students who worked with female animated agents had higher self-efficacy than students with male agents, provided that the female agents were rated as less intelligent and knowledgeable than the male agents. In a recent study on the effects of examples on student performance and self-efficacy, Huang (2017) designed and tested four types of examples: textual worked examples (standard vs. erroneous) and vicarious modeling examples (expert and masterly modeling vs. peer and coping modeling). Results of the study showed that while, of the four conditions, expert modeling examples were superior in promoting knowledge retention and transfer, peer modeling examples, whose expertise was more similar to the students', were most effective in fostering self-efficacy.

Near-peer mentors: definition and roles

In accordance with the model-observer similarity hypothesis, we define near-peers as a relationship between a mentor and mentee, who are proximal in age but somewhat distant in expertise (Clarke-Midura et al., 2018). To illustrate the expertise gap between the near-peer mentors and mentees, an analogy can be drawn to the ranks of workers: apprentices, journeymen, and masters. That is, the mentees are analogous to apprentices, who are new to a field of work and learning to develop their expertise. On the other hand, the mentors are parallel to journeymen, who have acquired expertise to some level but have to expand it in order to be deemed as masters. We argue that such expertise distance between the near-peer mentors and mentees would grant the mentors an ample knowledge base to aid the mentees as well as to substantiate their status as models. Furthermore, this difference would also heighten the mentees' perceived similarity to the mentors and make the mentors/role models more comparable and emulatable.

In terms of their roles in the near-peer mentorship, the near-peer mentors do not only offer assistance and guidance to the mentees, but, more importantly, they are also a vital source of vicarious influence that affects the mentees' self-efficacy in doing coding. By their behaviors and expressed ways of thinking, the near-peer mentors modeled for the mentees (a) a positive attitude toward CS (i. e. attitude modeling), (b) the skills and strategies requisite for the mastery of programming (i.e. performance modeling), and (c) programming as a social and collaborative activity that is less intimidating than one expects (i.e. event modeling). According to Bandura (1997), the undaunted attitude of a model can impart a high sense of self-efficacy to the observer to confront the difficulties. Acquisition of skills and coping strategies can raise self-efficacy expectations. In addition, a modeled event can inform the observer of the nature of the event, its level of difficulties, and its manageability, all of which affect self-efficacy expectations.

As a distinguishing feature of the model, vicarious modeling benefits the mentees' self-efficacy in several ways. The obvious benefit is that the addition of vicarious modeling enriched the sources of information learners could use to assess their capabilities. A second, and more important benefit, is that vicarious modeling served as an entry point especially for novice learners and also those who have had few successful programming experiences. As discussed above, modeling can raise novice learners' beliefs in their ability to do programming and ease them into the programming activities. Modeling can also neutralize the negative effects of previous failures on the learners' efficacy beliefs (Bandura, 1997). Another benefit associated with vicarious modeling is that it provided learners with a social platform where a trusting relationship between the near-peer mentor and mentees could develop through social comparisons. Specifically, being socially comparable would highlight the near-peer models' credibility as role models. Such credibility would subsequently translate into the mentees' perceived social relationships with the near-peer mentors, with the mentees endorsing their mentors as relatable and approachable (Clarke-Midura et al., 2018).

In sum, we argue that mentors of similar age and slightly more expertise would positively influence the mentees' self-efficacy. By controlling near-peer mentors' programming expertise and their age difference to the mentees, the near-peer mentoring model would be able to augment the perceived similarity between the mentors and mentees and increase the force of the mentor modeling effect on the mentees' self-efficacy. In turn, the enhanced self-efficacy would lead to an increment in intrinsic interest in computer programming.

In order to test the effectiveness of the mentoring model and its proposed mechanism (perceived similarity to the mentor in computer programming competence and mentor modeling), we addressed the following research questions:

1. To what extent does participating in the near-peer mentoring model affect mentees' self-efficacy in computer programming?
2. To what extent does the vicarious experience (i.e. mentoring modeling and perceived similarity to the mentor in computer programming competence) with the near-peer mentors exert its influence on the mentees' self-efficacy?

Method

Research design

This study used a pre- and post-test design, where we administered two surveys to collect students' efficacious beliefs in their abilities to program before and after the camp and their vicarious experience with their mentors during the camp. See the following section for more details about the surveys.

Background and context

We have been running summer camps since 2015, where we used the near-peer mentoring model to teach middle-school aged youth to program with App Inventor (see Clarke-Midura et al., 2018; Clarke-Midura, Sun, Pantic, Poole, & Allan, 2019). During the summer of 2018, we held five camps: one mentor training and four App Camps for middle-school-aged youth. The mentor training occurred over five days, for six hours a day (30 hours total). The App Camps also lasted five days for three hours a day (15 hours total). During the App Camp, middle school campers learned to program apps using App Inventor with the aid of high-school near-peer mentors. The purpose of the App Camp was to create a social avenue where a brief encounter with near-peer role models would motivate changes in campers' affective attitudes toward CS, and help them envision their future selves and CS as a possible career.

Mentor selection and training

Mentors filled out an application that asked why they wanted to be a mentor. Mentor age and their affective attitude toward CS were weighted over other factors such as past mentoring and programming experiences. For the year of 2018, we selected eighteen students to be mentors (5 males and 13 females, average age = 15). Eight mentors had previous programming experience, but none had experience with App Inventor. None of the mentors had experience with App Inventor. Mentor ethnicities included Asian/Pacific Islander (n = 2), Latina/o (n = 1) and Caucasian (n = 15). Twenty-two percent of the mentors reported being on free or reduced lunch.

Mentor training consisted of content and pedagogy training activities. The curriculum was presented in Canvas, a learning management system, with instructions on programming each app. The curriculum was the same as that for the campers. During camp, the content expert on site (i.e. a female CS faculty member) conducted mini-lectures on key programming concepts such as procedures and indexes. Compared to the regular camps, the mentor training camp lasted longer, so the mentors had more time to work on their apps. Also, they were encouraged to share their apps and code. When they did, the camp facilitator would project their products on slides so that all the others could see and comment. Mentoring efficiency was another consideration of the mentor training camp. Group activities were designed to train the mentors how to effectively communicate and offer assistance. There were also discussions concerning good and bad mentoring practices.

Research participants and camp design

We recruited 107 campers to attend our camps, and 106 participated in the study. Camper ages ranged from 9 to 14 years (average age = 12). Four campers reported to be of Hispanic or Latin origin. Camper racial makeup included 7% Asian (n = 7), 2% Black/African American (n = 2), 5% Native American (n = 5), 75% White (n = 80), 6% Multi-racial (n = 6), and 6% reported their race as Other (n = 6). Nine campers did not take the post-survey. In other words, we only had 97 observations for the post-camp measures (38 males and 59 females). Fifteen percent of our campers reported being on free or reduced lunch and this information was used only for the purpose of delineating our sample as well as the population they represent.

The App Camps were designed so that they provided either a female-only or mixed-gendered context. For the single gender camp, both the mentors and campers were female; the mixed-gender camps introduced males as either mentors or campers, or both. During the summer of 2018, we held one single-gendered and three mixed-gendered camps. Based on their gender and availability, mentors were assigned to one of the camps. Due to a surge of camp enrollments after we hired our mentors, two mentors were assigned to two camps whereas all other mentors only mentored one camp each. Gender composition and camp information are presented in Table 1.

Measures and data collection

Data used in this study were collected from a pre- and post-survey measuring campers' self-efficacy in computer programming and their perceptions of competence similarity to the mentors and mentor modeling acts. We administered an affective survey on computer programming prior to the start of the camp (PRE) and at the end of the camp (POST). The affect survey was adapted from

Table 1. Description on the contexts of camps and mentors and campers at each camp (N_{mentor} = 18, N_{camper} = 106).

Camp	Context	Mentor	N_{mentor}	Camper	N_{camper}
1	Mixed-gender	Mixed-gender	5 (2 M, 3 F)	Female-only	29 (29 F)
2	Mixed-gender	Female-only	6 (6 F)	Mixed-gender	33 (21 M, 12 F)
3	Mixed-gender	Mixed-gender	6 (3 M, 3 F)	Mixed-gender	27 (20 M, 7 F)
4	Female-only	Female-only	3 (3 F)	Female-only	17 (17 F)

Note: Two female mentors mentored two camps.

existing measures (Carrico & Tendhar, 2012; Fennema & Sherman, 1976). We rephrased the questions to focus on computer programming. In the present study, we focused on the self-efficacy items.

In order to measure camp experience, the research team developed items examining mentees' perceived mentor modeling effects and mentees' perceived similarity to mentors in regard to programming competence. These modeling questions were developed based on Schunk's (1987) definition of modeling. That is, modeling is a process in which a model's (in our case, the near-peer mentors) behaviors, expressions, and verbalizations were attended to by the observer (i.e. the mentees) and resulted in their behavioral changes. The modeling questions had four items, such as 'Watching my mentor made me want to program' and 'My mentor made me want to program.' The perceived similarity questions consisted of three items, measuring mentees' perceived closeness of programming competence (1 item, 'In terms of programming skills, my mentor and I are the same.') and superiority or inferiority of their own programming competence relative to the mentors' (2 items, 'In terms of programming skills, I am better than my mentor.' and 'In terms of programming skills, my mentor is better than me.').

As we tested the inter-item correlations between the perceived similarity questions, we found, surprisingly, that the perceived closeness item was significantly correlated to the superiority question (i.e. In terms of programming skills, I am better than my mentors), $r = .377$, $p < .001$. This suggests that the two items are not exclusive to each other in measuring perceived competence similarity and difference. In other words, the disagreement with the statement, 'I am better than my mentors', may denote either competence similarity or mentor superiority. Given the two items' validity issues and our interest in the role of perceived similarity in modeling, we removed the superiority and inferiority questions and only used the perceived closeness question (i.e. In terms of programming skills, my mentors and I are the same.") in the following analyses. All the questionnaire items used 8-point Likert scales (1 = strongly disagree to 8 = strongly agree).

Data analysis

The analysis proceeded through a multistep process. Data were first screened for missing data, normality, and outliers. Normality test showed that baseline self-efficacy, perceived similarity, and mentor modeling were approximately normal, while post-camp self-efficacy were skewed. Therefore, we transformed the skewed data using reflection methods. See Table 2 for the distributional properties of the variables of interest before and after data transformation.

In addition, we conducted factor analyses on self-efficacy and mentor role modeling to test their psychometric properties. Results of principal component analyses (PCAs) indicated unidimensionality for both scales. Inter-item reliabilities of the two scales were then computed using Cronbach's alpha. Results are presented in Table 3.

Table 2. Distributional properties of the variables of interest before and after data transformation.

Variable	Skewness (S.E.)	Kurtosis (S.E.)
Raw data		
Self-efficacy pre	−.11 (.24)	−.56 (.47)
Self-efficacy post	−.82 (.25)	.45 (.49)
Perceived similarity	.36 (.25)	−.60 (.49)
Mentor modeling	−.58 (.25)	−.11 (.49)
Transformed data		
Self-efficacy post	−.40 (.24)	−.17 (.24)

Prior to the final analyses of interest, we fit mixed-effect models (i.e. hierarchical linear models [HLM] or multilevel models) using the transformed data to test the possibility of camp effect, camper gender effect, and their interaction on post-camp self-efficacy with the baseline scores as covariates. In order to test the cluster effect, we first fit the intercept-only models with no predictor variables but only the baseline scores as covariates. The intra-class correlation for self-efficacy was negligible (i.e. $\rho < .001$), suggesting that controlling for the baseline scores, camp membership did not have an effect on the post-camp self-efficacy scores. We then introduced camper gender and (camper gender)×(-camp membership) to the model. Results indicated that camper gender and its interaction with camp membership did not have significant effects on post-camp self-efficacy (gender: $t(92) = -.61$, $p = .541$; interaction: $t(92) = -.74$, $p = .460$). Therefore, we pooled the data in the following analyses.

We fit longitudinal mixed-effect models to detect the intervention effects on campers' self-efficacy in programming. As there was no camp effect, the data in the form of repeated measures was nested within individual level as the highest level. One advantage of longitudinal mixed-effect models over the conventional statistical techniques such as *t*-test and its non-parametric equivalents lies in mixed-effect models' ability of handling missing data (Finch, Bolin, & Kelley, 2014; Hox, 2010). While testing the model, we used the raw scores of baseline and post-camp self-efficacy for the following reasons: (a) post self-efficacy was moderately skewed, and (b) maintaining consistent data structure so as to make result interpretation simple and easy.

In order to test mentor modeling and perceived similarity effects on post-camp self-efficacy, we fit a moderation model with mentor modeling as the independent variable, perceived similarity as the moderator, post-camp self-efficacy scores as the outcome variable and baseline self-efficacy as the covariate. All the linear models were fitted in R (R Core Team, 2013) using the package

Table 3. Cronbach's alphas for self-efficacy and mentor modeling.

Variable	Pre	Post
Self-efficacy	.85	.85
Mentor modeling	N/A	.87

'lmerTest' (Kuznetsova, Brockhoff, & Christensen, 2017) and restricted maximum likelihood (REML) for mixed-effect models and maximum likelihood (ML) for the moderation model.

Results

RQ1. To what extent does participating in the near-peer mentoring model affect mentees' self-efficacy in computer programming?

Results of the HLM analysis showed that time was a significant predictor, $p < .001$. In addition, the positive correlation coefficient ($\pi = 1.29$) indicated that on average self-efficacy increased by 1.29 units from pre- to post-camp. Descriptive statistics of the raw self-efficacy scores are presented in Table 4.

RQ2. To what extent does the vicarious experience (i.e. Mentoring Modeling and Perceived Similarity to the Mentor in Computer Programming Competence) with the near-peer mentors exert its influence on the mentees' self-efficacy?

In order to answer this question, we fit a moderation model to mentor modeling, perceived competence similarity, and self-efficacy. Results of the moderation model were significant, $F(4, 90) = 21.29$, $p < .001$, adjusted $R^2 = .46$. In addition, after accounting for the pre-camp self-efficacy differences, mentor modeling and perceived competence similarity were both significant predictors, $t_{modeling} = 2.25$, $p = .027$; $t_{similarity} = 2.52$, $p = .013$. The interaction between mentor modeling and perceived competence similarity was also significant, $t = 2.19$, $p = .031$. See Table 5 for the model outputs. We also plotted to check the interaction effect on post-camp self-efficacy while setting baseline self-efficacy to its mean (see Figure 1).

As Figure 1 shows, modeling effect on self-efficacy is conditional on perceived competence similarity – perceived similarity augments modeling effect. Specifically, when the mentees do not deem their programming skills similar to the mentors, their self-efficacy would barely change despite mentor modeling. Conversely, when the mentees perceive a similarity between themselves and the mentors in programming skills, their self-efficacy would increase as mentor modeling intensifies. By comparison, the more similar, the greater the model effect on self-efficacy.

Table 4. Descriptive statistics of self-efficacy at pre- and post-camp ($N_{pre} = 106$; $N_{post} = 97$).

	Pre-camp		Post-camp	
Variable	Mean	SD	Mean	SD
Self-efficacy	4.64	1.71	6.00	1.52

Table 5. Model estimates, confidence intervals and R^2 changes.

Variable	B (S.E.)	β	95%*CI*	ΔR^2
Pre Self-efficacy	.51 (.07)**	.57	[.372, .650]	.38
Mentor modeling	.17 (.08)*	.17	[.020, .329]	.04
Perceived similarity	.16 (.06)*	.20	[.034, .285]	.04
Modeling × Similarity	.08 (.04)*	.17	[.008, .160]	.03

$^{**}p < .001$, $^{*}p < .05$

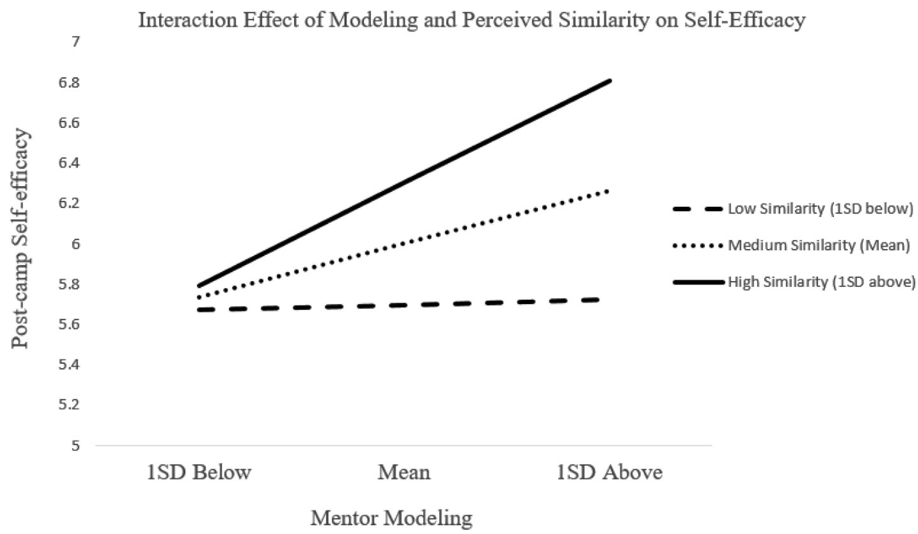

Figure 1. Mentor modeling effect on post-camp self-efficacy conditional on perceived competence similarity while setting baseline self-efficacy to its mean.

Discussion

The purpose of the study was twofold: (a) to examine the efficacy of a near-peer mentoring model on improving the mentees' self-efficacy in computer programming, and (b) to link the changes, if any, in self-efficacy to the enhanced vicarious experience modeled by the near-peer mentors. Operationalized as perceived similarity in programming competence and mentor modeling, we argued that the vicarious influence from the near-peer mentors would positively affect the mentees' self-efficacy. Specifically, it was hypothesized that by controlling the differences in age and expertise between mentors and mentees, the near-peer mentoring model would increase the mentees' perceived similarity to their mentors in respect to programming competence and also strengthen the force of the modeling effect. Findings showed that self-efficacy indeed increased from pre- to post-camp, suggesting the efficacy of the near-peer mentoring model on enhancing affective attitudes toward programming.

Our findings also shed light upon how the near-peer mentoring model may have worked to improve the mentees' programming self-efficacy. We hypothesized based on Bandura (1977, 1997) that (a) mentor modeling, as a source of vicarious influence, would increase mentees' self-efficacy and (b) mentees' perceived competence similarity to the mentors would moderate the modeling effect. Results of the moderation model showed that mentor modeling did significantly contribute to post-camp self-efficacy. In addition, perceived competence similarity was found consistent with our hypothesis, namely, perceived competence similarity enhances modeling effect on self-efficacy, and lack of such similarity negates modeling effect. This finding is consistent with the literature on model-observer similarity and vicarious modeling (Braaksma, Rijlaarsdama, & van den Bergh, 2002; Huang, 2017; Selzler et al., 2020; Zimmerman & Kitsantas, 2002). The relative weak correlations between modeling, its interaction with perceived competence similarity, and post-camp self-efficacy (βs = .17) are not surprising, because as Bandura (1977, 1997) predicted, self-efficacy is also susceptible to the influences of other informational sources such as enactive experience, verbal/social persuasion, and physiological states, and enactive experience can override the effects of other sources. Therefore, future studies may focus on how the near-peer mentoring model may have influenced those sources to change self-efficacy in combination with the vicarious experience.

Despite their (i.e. modeling and its interaction with perceived competence similarity) limited contributions to the observed variance of post-camp self-efficacy, our findings, however, have an important practical significance that is not captured by those variance statistics. In other words, our findings on modeling and its relationship to perceived similarity have important implications for programs that set out to recruit youth, particularly girls, into CS. As acknowledged across CS literature, role models play an important role in recruitment (e.g. Ashcraft, Eger, & Friend, 2012; McGrath & Aspray, 2006). Accordingly, a plethora of CS initiatives have incorporated role model exposure opportunities into their intervention procedures (Franklin, Conrad, Aldana, & Hough, 2011; Graham & Latulipe, 2003; Khoja et al., 2012; Outlay, Platt, & Conroy, 2017; Vachovsky et al., 2016). However, not all these exposure procedures have produced the desired results due to the lack of perceived similarity. For instance, one study (Bamberger, 2014) reported a program that aimed to encourage secondary school girls to pursue a STEM career by exposing them to female role models working in those fields. Its findings, however, indicated that the exposure experiences had negative effects on girls' confidence in dealing with STEM and pursuing STEM careers, which was attributed to the cognitive and developmental gaps between the girls and role models. In summary, our findings suggest that perceived similarity in age and especially competence is an important consideration for mentoring initiatives, especially for those that use mentors as role models to broaden the participation of underrepresented groups.

Our study has a few notable limitations. We only focused on perceived age and expertise proximity and ignored the potential impacts of other mentor attributes such as gender and ethnicity or race on mentees' vicarious experiences. According to the model-observer similarity hypothesis, gender match and ethnicity or race match may also reinforce mentors' vicarious influence on mentees' efficacious beliefs. Although a number of researchers have investigated this topic, results of gender match on students' vicarious learning are not only inconsistent but also contradictory (e.g. Bamberger, 2014; Hoogerheide et al., 2016; Lockwood, 2006; Marx & Roman, 2002). For example, while Lockwood (2006) showed in one of her studies the positive effect of same-gender models on female students' career-related motivational beliefs, Bamberger (2014), as mentioned above, found that same gender role models had a negative effect on students' confidence. In addition, the null effect of gender match on self-efficacy was also observed in two recent studies (Hoogerheide et al., 2016, 2016). In addition to gender match, there is also empirical evidence suggesting the benefits of ethnicity or race match in minority students' learning outcomes and the quality of their relationships with the mentors (e.g. Rhodes, Reddy, Grossman, & Lee, 2002; Spencer, 2007). However, to the best of our knowledge, no research has examined the relationship between ethnicity or race match and peer mentors' vicarious influence on mentees' self-efficacy. As such, we need to conduct further studies to investigate how gender match and ethnicity or race match may influence mentors' modeling effect, whose results will add to the youth mentoring literature and advance our knowledge of these two topics (i.e. gender match and ethnicity or race match) from the perspective of vicarious learning.

There are a few additional areas worthwhile of further explorations in future studies. First, we only investigated the effect of the near-peer mentoring model on novice learners who had little previous knowledge. Researchers in the future can test the model's effectiveness using a different population such as more experienced learners. Second, researchers may want to investigate whether some environmental factors such as mentees' social economic status interact with perceived similarity to influence mentors' modeling effect. Third, if researchers conduct research on the model's long-term effects on self-efficacy, interest, performance, and achievement, it may broaden current understandings of the model we presented.

Conclusions

Despite efforts over the past three decades, broadening participation in CS is still a national priority (e.g. National Science Board, 2018). In response to this call, we offer a near-peer mentoring model in the expectation of addressing the underrepresentation issue. In this model, we utilized the near-peer mentors/models to enhance the mentees' vicarious experience in order to increase their self-efficacy in computer programming. Findings showed that this model was effective in raising mentees' self-efficacy, suggesting its potential to recruit youth to CS. This study also provided an empirical explanation as to in what ways the near-peer mentors vicariously contributed to the changes in the mentees' self-efficacy. These findings have important implications for other mentoring programs that focus on promoting youths' academic and career interest. We have demonstrated that in addition to leveraging the mentors' modeling effect, the perceived similarity between a mentor and mentee is also an important factor to consider for program designs. In other words, in order to argument their modeling effects, mentors do not need to be experts but should have a slightly higher proficiency in the subject than mentees.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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