PROJECT SUMMARY

Overview. Who can considers themselves to be an expert in and who can study and later work in computer science (CS) are essential questions for individuals in a democratic society, especially in light of the role of CS and computing and digital technology more broadly in so many areas of contemporary life. Past research has shown that there exists a substantial difference in who pursues an interest, a major, or an occupation in CS and others, particularly for female individuals and for people of color (Sax et al., 2017). Moreover, research has shown that some overall factors, such as competence-related beliefs and co-curricular supports, might begin to explain these differences (e.g., Lishinski, Yadav, Good, & Enbody, 2016). However, scholars have not adequately addressed what drives these differences at the level at which policymakers and educators seeking to support and sustain a more representative population of CS experts can most effectively act, namely, *at a situation-to-situation level*, rather than in terms of what happens in courses, programs of study, or occupations *in general and overall*. What drives differences in who pursues CS may be due, then, to situation-specific factors, such as experiences that spark students' interest in the domain, that have not yet been the focus of study. The proposed project would address this gap through examining how a specific, key outcome, sustained, individual interest in CS, develops from finer-grained, situational interest, through the use of a novel (in CSEd) methodology, experience sampling (or ESM; Hektner, Schmidt, & Csikszentmihalyi, 2007). This study is carried out in the context of an introductory undergraduate computer science (CS) course (for majors and non-majors) at a large, Southeastern United States, research-intensive university with around 175 students. This proposed study is framed in terms of interest development, particularly to understand how students' in-the-moment interest is sparked in specific situations and then accumulates into more ongoing and sustained individual interest. This method involves asking individuals to respond to short, regularly occurring surveys about their experiences in the course (via a text message sent to them) after each class. Thus, how students' initial interest, as well as their individual characteristics, such as their initial interest and their CS self-concept, relate to students' situation-to-situation interest (as measured via ESM) can be queried. Further, how contextual factors - those internal to students, such as how challenging they perceived each class' activities to be, as well as those external to students, such as the focus of each class - relate to students' situational interest can also be explored. Finally, how students' situational interest relates to changes in their longer-term, individual interest, can also be better understood.

Intellectual Merit. Particularly as scholars in related fields argue that a *watershed*, rather than a *pipeline*, may be a more generative way of looking at who pursues a STEM major (National Academies of Sciences, Engineering, and Medicine, 2018), understanding what contextual factors impact the development of interest at a fine-grained level has the potential to generate new accounts of how students pursue CS majors. The proposed project also has the potential to contribute foundational knowledge about how interest develops in a domain—CS—in which the phenomenon of interest development has not yet been studied. Additionally, the project has the potential to contribute to interest development theory, which posits that situational interest changes, over time, into well-developed individual interest, yet which has not been studied with an approach (such as ESM) suitable for understanding situational interest.

Broader Impacts. This proposed work has the potential to inform the conversation about how to expand access to and broaden participation in computing through revealing which factors, such as particular instructional practices or experiences, are most critical for educators and administrators to target. This work also has the potential to bolster the capacity for others at my institution—and in similar higher education contexts—to carry out impactful research in CS education, particularly the Chair of the CS department, the post-doctoral scholar, the graduate students, and the undergraduate students involved in the project. This work has the potential to contribute to debates on what factors may explain differences in who pursues, is supported, and sustains computing and technology and careers. Finally, this work has the potential to bolster the potential for researchers in CSEd and in other fields to make use of a new data collection approach, the ESM, and an associated data analytic technique.

Understanding the development of interest in computer science: An experience sampling approach

Joshua Rosenberg, University of Tennessee, Knoxville

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1. FUNDAMENTAL STEM EDUCATION RESEARCH TOPIC

1.1 Who is an expert and who participates in computer science

Who can consider themselves to be an expert in and who can study and later work in computer science (CS) are essential questions for individuals in a democratic society, especially in light of the role of CS and computing and digital technology more broadly in so many areas of contemporary life. While undergraduate students majoring in computer science have increased (National Academies Press, 2018), issues around how accessible the CS domain is an issue that has persisted since computing-related careers became lucrative (Lewis, Shah, & Falkner, 2019).

Past research has shown that there exists a substantial difference in who pursues an interest, a major, or an occupation in CS and others, particularly for female individuals and for people of color (Sax et al., 2017). Moreover, research has shown that some overall factors, such as competence-related beliefs and co-curricular supports, might begin to explain these differences (e.g., Lishinski, Yadav, Good, & Enbody, 2016). However, scholars have not adequately addressed what drives these differences at the level at which policymakers and educators seeking to support and sustain a more representative population of CS experts can most effectively act, namely, *at a situation-to-situation level*, rather than in terms of what happens in courses, programs of study, or occupations *in general and overall*.

What drives differences in who pursues CS may be due, then, to situation-specific factors, such as experiences that spark students' interest in the domain, that have not yet been the focus of study. In terms of research, this gap in the literature, as depicted in Figure 1, is essential to address because it means that potential solutions to the question of who is an expert in and who studies CS may not target the situational factors, such as specific learning activities, time spent with mentors in the discipline, and experiences that spark interest in CS, that matter most. Moreover, these situational may factors may have an important role in terms of shaping the development of students' longer-term interest (or a predisposition to re-engage with the ideas and practices in a particular domain) in CS.

Figure 1. How interest in CS develops in specific contexts is not well-understood.

1.2 The need to understand how interest in CS develops

A fundamental challenge for STEM education research, in particular, is to understand how interest develops and is sustained or enhanced over time in a situation-to-situation way. This challenge is made more difficult because interest development has not been studied in such a way yet in CSEd. Moreover, in terms of research methodologies, traditional designs have not been able to study or take into account what shapes interest, not at a general (i.e., semester-, year-, or program-long) level, but a more specific, situation-to-situation level. Particularly in light of efforts to support broader access to and participation in CSEd (The White House, 2016), understanding how interest develops in the context of specific learning experiences in terms of students' *situational interest* may shed light on important, under-explored factors which can be the focus of the design of curricula (and co-curricular supports) and subsequent supports for CS students.

2. PROPOSED PROJECT

2.1 Summary of the proposed project

The proposed project would address this gap through examining how a specific, key outcome, sustained, individual interest in CS, develops from finer-grained, situational interest, through the use of a novel (in CSEd) methodology, experience sampling (or ESM; Hektner, Schmidt, & Csikszentmihalyi, 2007). This study is carried out in the context of an introductory undergraduate computer science (CS) course (for majors and non-majors) at a large, Southeastern United States, research-intensive university.

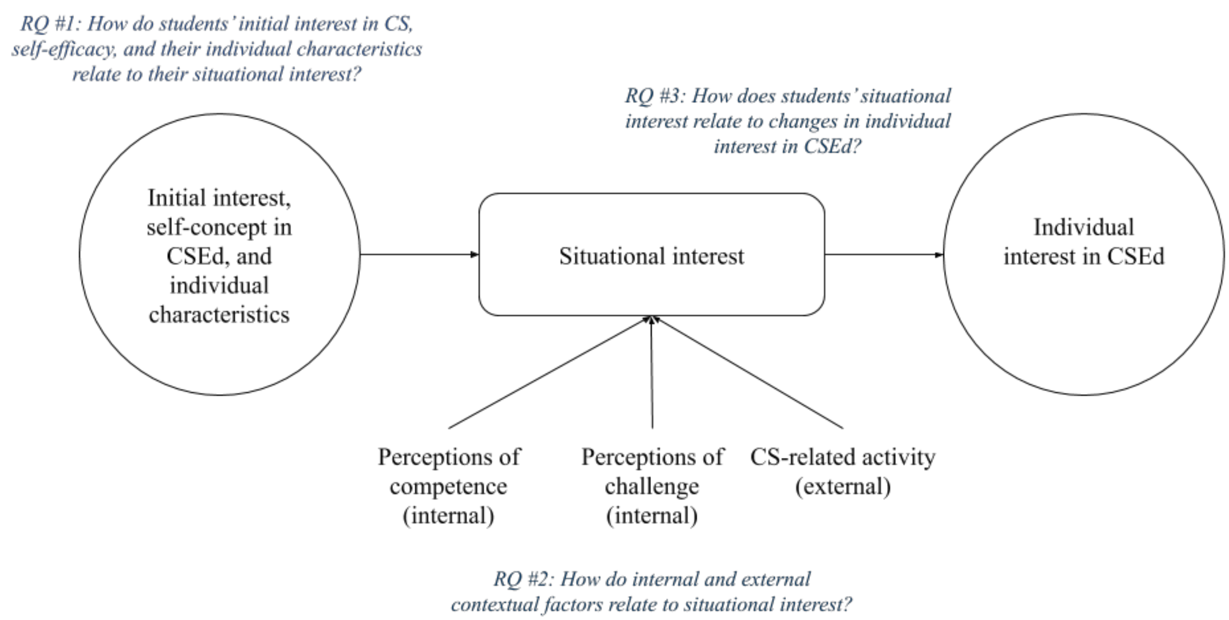
This proposed study is framed in terms of interest development, particularly to understand how students' in-the-moment interest is sparked in specific situations and then accumulates into more ongoing and sustained individual interest. This method involves asking individuals to respond to short, regularly occurring surveys about their experiences in the course (via a text message sent to them) after each class. Thus, how students' initial interest, as well as their individual characteristics, such as their initial interest and their CS self-concept, relate to students' situation-to-situation interest (as measured via ESM) can be better understood. Further, how contextual factors - those internal to students, such as how challenging they perceived each class' activities to be, as well as those external to students, such as the focus of each class - relate to students' situational interest can also be explored. Finally, how students' situational interest relates to changes in their longer-term, individual interest, can also be better understood.

This proposed study also employs a novel data analytic technique, namely, the use of a multivariate modeling approach that accounts for the ways in which ESM responses are grouped, or nested, within students, as well as specific situations (e.g., Houslay & Wilson, 2017). This would allow for responses collected via ESM to be related to longer-term outcomes—in the present case, students' interest in CS. Thus, this proposed study aims to study individual students' repeated experiences in CS in a more contextualized way, through an experience sampling approach. In all, then, this proposed study would have interconnected substantive (understanding the development of interest among undergraduate CS majors) and methodological objectives (making use of ESM data and analyzing the data using a novel analytic approach).

Thus, the following research questions (as represented in Figure 2) will be addressed in the proposed study:

- RQ #1: How do students' initial interest in CS and their individual characteristics (self-concept in relation to CS, gender, major/non-major status, and self-identification with a racial or ethnic social group) relate to their situational interest?
- RQ #2: How do internal (e.g., perceptions of challenge and competence) and external (e.g., the CSEd related activity) contextual factors relate to situational interest?
- RQ #3: How does situational interest relate to changes in individual interest in CS?

Figure 2. The basic of interest development, as used in this study.



2.2 Intellectual merit

Particularly as scholars in related fields argue that a watershed, rather than a pipeline, may be a more generative way of looking at who pursues a STEM major (National Academies of Sciences, Engineering, and Medicine, 2018), understanding what contextual factors impact the development of interest at a fine-grained level has the potential to generate new accounts of how students pursue CS majors. The proposed project also has the potential to contribute foundational knowledge about how interest develops in a domain—CS—in which the phenomenon of interest development has not yet been studied. Additionally, the project has the potential to contribute to interest development theory, which posits that situational interest changes, over time, into well-developed individual interest, yet which has not been studied with an approach (such as ESM) suitable for understanding situational interest.

2.3 Broader impacts

This proposed work has the potential to inform the conversation about how to expand access to and broaden participation in computing through revealing which factors, such as particular instructional practices or experiences, are most critical for educators and administrators to target. This work also has the potential to bolster the capacity for others at the investigator's institution—and in similar higher education contexts—to carry out impactful research in CS education, particularly the Chair of the CS department, the post-doctoral scholar, graduate students, and undergraduate students involved in the project. This work has the potential to contribute to debates on what factors may explain differences in who pursues, is supported, and sustains computing and technology and careers. Finally, this work has the potential to bolster the potential for researchers in CSEd and in other fields to make use of a new data collection approach, the ESM, and an associated data analytic technique.

3. THEORY AND PAST RESEARCH

3.1 Interest in computer science

Historically, it is not possible to disentangle interest in computer science without considering who has access to the field and who is supported in their pursuit of CS. In a pioneering work, Margolis and Fisher (2003) studied the experiences of women CS students at a research-intensive university and found that there were early experiences in students' majors that may have affected interest in CS; for instance, female students perceiving that they were not as competent as their male peers, who may have entered their major with greater experience using personal computers at home. After a highpoint of female students' enrollment in computer science around the mid-1980s, their enrollment has declined through the early 2000s (Sax et al., 2017): The most recent data suggests that just around 20% of students who complete a CS degree are women.

There is some evidence that interest is impacted by features of the instructional and institutional context for CSEd. Margolis, Fisher, and Miller (2000) suggested that it is not the nature of CS or differences in interest in CS that drive some of these gendered differences in CS interest, but, rather, "social and cultural expectations within the field that discourage girls and women" (p. 125). When female students enter classes that are male-dominated or taught primarily by male instructors, they may perceive that they do not belong. Margolis et al. (2000) reported on an undergraduate student who, after finishing a day in high school, would return home to program. In college, this same student, discouraged by interactions with peers and instructors, no longer programmed in her leisure time after the undergraduate courses she was taking—and later she chose to pursue a non-CS major.

Research suggests that multiple motivational factors, particularly competence-related beliefs (such as self-efficacy), may shape achievement in CSEd (Lishinski et al., 2016; Wilson, 2002). However, less research has been done to study how interest is either an antecedent or an outcome of motivational factors.

3.2 How does interest develop?

Contemporary interest development theory suggests that interests emerge from the interactions of an individual in a particular environment rather than residing completely within an individual (Hidi & Renninger, 2006; Prenzel, 1992). Thus, this proposed work would align with the work in CsEd of

Margolis et al. (2000). Hidi and Renninger (2006) described a helpful framework for understanding the development of interest: that moment-to-moment experiences can spark *situational interest* that can, over time, develop into an *individual interest* in a topic or discipline. Thus, from the perspective of interest development, a more enduring individual interest can develop as a result of the repeated experience of situational interest—a more fleeting interest in a specific activity or task that is typically characterized by immediate positive affective reactions to the immediate activity at hand, but may or may not be sustained over time).

Hidi and Renninger (2006) described individual interest as "a relatively enduring disposition to re-engage particular contents over time" (p. 111). They and other contemporary theorists framed interest as the product of the interaction between a person and particular content, and as such, interest is content specific (Prenzel, 1992; Renninger & Wozniak, 1985). A person's individual interest in CSEd, for example, is the result of the way that person has interacted with CS ideas, practices, and content over time.

The interest of any individual youth in CSEd may also be influenced by societal norms and stereotypes about what types of people are interested in and qualified for particular domains. There continue to be persistent stereotypes about many CS fields as being "male" fields—and of girls and women being less capable than boys and men in CS areas of study (Hill, Corbett, & St. Rose, 2010). These persistent stereotypes and the implicit and explicit biases that emerge from them can influence the way boys and girls interact with CS content and their trajectories of interest development over time. Given existing gender-related stereotypes about CS disciplines (Hill et al., 2010), it is important to take gender into account in our examination. A similar argument might be made with respect to race and ethnicity, though recent data about how representative students in CS degrees are relative to the potential student body suggests that both male and female students who identify as black are a greater percentage of CS majors relative to the percentage of male and female students across all majors (Sax et al., 2017).

Students do not enter CS majors without some degree of interest. Indeed, students enter their majors with a certain level of interest, which itself is the result of prior opportunities for interaction with said content. Thus, it is likely important to account for students' individual level of interest at program entry.

Although the foundational work that led to the development of this theory was qualitative, most subsequent work has been more quantitative. This subsequent work has not explored the ways in which situational interest—cumulatively and on a moment-to-moment basis—leads to the development of enduring individual interest. Instead, most research has explored either situational *or* individual interest (e.g., Linnenbrink-Garcia et al., 2013) or has examined interest at only a few time points (e.g., Rotgans & Schmidt, 2011).

3.3 The challenge of measuring interest

Robins (2015) points out that there are some particular methodological challenges for those carrying out CSEd research, in part because many CSEd researchers come from CS backgrounds and departments, rather than departments in Colleges of Education. Scholars have argued that computer science has not borrowed as much from the learning sciences and educational psychology research—as well as educational researchers in other domains—as other fields such as physics and chemistry education research (Lishinski, Yadav, & Enbody, 2017). Thus, there may be some challenges to measuring educational psychology-grounded constructs such as interest, because there are relatively few instruments and few established measurement and analysis-related approaches.

Interest may be especially challenging to study because it has been conceptualized as a content- and context-dependent construct. Thus, it is a challenge to study interest using techniques—particularly for quantitative approaches—common to educational research, namely, self-report surveys. One methodological approach that has benefits concerning measuring interest in a context-sensitive way is ESM (e.g., Strati, Schmidt, & Maier, 2017; Turner & Meyer, 2000; Sinatra, Heddy, & Lombardi, 2015). ESM involves asking (usually using a digital tool and occasionally a diary) participants short questions about their experiences at regular intervals (Hektner et al., 2007). ESM is particularly well-suited to understanding the context-dependent nature of engagement because by collecting measures about learners' experience when signaled, students can answer questions within the context of their experience and are minimally interrupting from the activity they are engaged in(Hektner et al., 2007).

The ESM approach is both sensitive to changes in interest over time, as well as changes between learners; this allows us to understand how numerous factors impact engagement in nuanced and complex ways (Turner & Meyer, 2000). Although time-consuming to carry out, ESM can be a robust method of measurement that leverages the benefits of both observational and self-report data, allowing for both ecological validity and the use of closed-form questionnaires amenable to quantitative analysis (Csikszentmihalyi & Larson, 1987). Despite the logistic challenges of carrying out ESM in large studies, some scholars have referred to it as the gold standard for understanding an individual's subjective experience (Schwarz, Kahneman, & Xu, 2009).

Research has shown how the use of ESM can lead to distinct contributions to our understanding of other constructs, such as engagement. For example, Schneider et al. (2016) and Linnansaari, Viljaranta, Lavonen, Schneider, and Salmela-Aro (2015) examined features of optimal learning moments—that is, moments in which students report high levels of interest, skill, and challenge—as well as their antecedents and consequences. Surprisingly, scholars have not used ESM to study interest or interest development, apart from one study in the context of youths' enrollment in summer STEM programs (Schmidt, Rosenberg, Beymer, Naftzger, & Shumow, 2018). While ESM data is rich, it can also be challenging to analyze; mixed effects—or multi-level—models may be essential to use. For example, Strati et al. (2017) explored the relationship between engagement and measures of teacher support using cross-classified mixed effects models, finding associations between instrumental support and engagement and powerfully demonstrating the capacity of ESM to understand some of the context-dependent nature of engagement.

Similar to the modeling approach that Strati et al. made use of, Pöysä et al. (2017) used a similar data analytic approach as Strati et al. (2017)—that is, a crossed effects model for variation within both students and time points, both within and between days. These studies established the value of using ESM to understand the context-dependent nature of engagement. Additionally, these recent studies—particularly Strati and colleagues (2017)—show how effects at different levels, one that exhibits a familiar type of 'nesting' (i.e., responses within students) and one that exhibits a more atypical type (i.e., responses within specific situations) are treated. These considerations are key practical concerns for the analysis of ESM data, including data that can be used to understand how students' situational interest develops in the context of undergraduate CS classes.

4. RESEARCH PLAN AND TIMELINE

4.1 Context and participants

The context for this proposed study is an introductory computer science course at a large, Southeastern, research-intensive university that meets two times per week for one semester. Due to high rates of attrition, the department chair is interested in understanding students' experiences in the course better. Participants are to be recruited from approximately 200 students typically enrolled in the class. The students in this class are both majors and non-majors in CS (though the majority of students are majors). This is both an affordance and a constraint of this particular class context: students who are majors who enter the class with higher interest and self-concept than the average student in the class may find some of the course content to relate to ideas that they have studied and understood through former classes, whereas students new to CS may find the content very demanding. Thus, there is likely to be substantial variability in both the initial interest and self-concept of students and their experiences throughout the course. Moreover, there are likely to be different trajectories of interest development that students in the class experience because of the variation in their past experiences with CS. Finally, the chair of the department associated with the course has sought to provide tutoring to address attrition-related issues in the course but is seeking to improve the course in broader ways (and to provide more co-curricular supports for students). These efforts have not yet been systematic or based on information about students' experiences in the class; instead, they have been based on anecdotal evidence from both students and instructors.

4.2 ESM and survey measures

Three sets of measures will be used. One, the pre-post survey measure, will be used at the beginning and at the end of class. The second, the ESM survey measure, will be used after each class—though with a subset of all of the students. ESM measures will be sent to subsets of students (one-half of participants) after each class. The last measure will be used to understand the impact of an external contextual feature, the nature of the CS-related activity in each class.

- Pre-post survey measures will be administered in the first and second-to-last weeks of class. The pre-post survey will include questions on individual interest as well as demographic questions on students' self-reported gender, self-identification with a particular social group, and major/non-major status. The self-concept items will be adapted from the five items for self-concept scale from the Patterns of Adaptive Learning survey (Midgley et al., 2000).

- The ESM survey will be conducted via the text-message and web-based software, Survey Signal, and will include two items for students' situational interest (adapted from Linnenbrink-Garcia et al., 2010) as well as two items for students' enduring interest and challenge adapted from other studies using ESM (e.g., Strati et al., 2017). In addition, students will be asked if they have any other questions or comments.

- In addition to the survey measures, measures of in-class activities will be determined based on collecting a short written report of the day's activities from the instructor for the class. In particular, a taxonomy of common activities used in past research (Naftzger, Schmidt, Shumow, Beymer, & Rosenberg, 2019) will be adapted for use in the present study. While the class is primarily lecture-based, it has involved a variety of activities, including in-class coding exercises, following along with live-coding by the instructor, and responding to short, embedded questions, in addition to lectures.

4.3 Data analysis approach

A number of methods have been proposed for studying how momentary engagement experiences impact longer-term changes in key outcomes such as interest—including simply averaging students' experiences (which may ignore too much important information) and mixed effects (which, past research has pointed out, both have limitations with respect to the specific goal at hand). Despite this part work, there is currently an opportunity to make use of methods from outside STEM education, particularly to address some of the shortfalls of past methods that have been used in STEM education to study how situation-to-situation outcomes, such as situational interest, lead to changes in longer-term outcomes. In this proposed project, the investigator will test and use an approach that combines the strengths of mixed effects models, through the use of a model that combines the strengths of both—a multivariate, mixed effects model (Houslay & Wilson, 2017). This model considers the relationship between situational interest—as measured through ESM—and individual interest—measured at the end of a semester—as two outcomes (i.e., a multivariate outcome). It also recognizes that the ESM responses are associated with a specific individual and so considers the individual student to be a grouping factor (i.e., a level) in the data. Finally, because each class may be associated with particular, systematic differences in situational interest, each class is considered as another group factor (i.e., level), in the data.

4.4 Study procedure

At the start of the semester, students will be invited to participate via an in-class announcement by the PI. Then, students will receive an email and consent information with the first survey. Between five minutes and three hours after each class, a randomly selected one-half of all consenting students will be signaled—using the Survey Signal software—with a link to a short Qualtrics survey that will take approximately 10 minutes to complete. One-half of all participants (instead of all of the participants) will be signalled in order to not over-burden the students or to distract them from the course, other courses, and other activities. The one-half of students will be randomly selected so that students who typically communicate after the course will not always be signalled at the same time, which could contribute a source of bias to the data (i.e., if students always report that they are more interested because of the peer with whom they spend time). Finally, the surveys will be sent at different times to different students after each class to mitigate against the risk that some students have commitments immediately after the class. Finally, in the second to last week of the course, students will be signaled to respond to the post-survey. This post-survey should take approximately 10 minutes to complete.

4.5.1 RQ #1: How do students' initial interest in CS and their individual characteristics (self-concept in relation to CS, gender, major/non-major status, and self-identification with a racial or ethnic social group) relate to their situational interest?

This question concerns how students' characteristics upon entry to the course impact their situational interest. Note that the characteristics of students will be measured using a self-report survey during the first week of the class, whereas situational interest will be measured using ESM. Thus, this analysis involves connecting student-level data to data collected via ESM that has multiple responses per student. Accordingly, answering this question involves the use of a mixed effects model estimated with the lme4 R package (Bates et al., 2015). A "bottom-up" model-building process will be used, in which increasingly complex models are estimated, with the models compared to simpler models to determine whether the model explains students' situational interest better than the earlier models.

The first model will be a variance components model—that is, a model with only the grouping factors (i.e., indicators for the student and the specific day of class) included. This model will reveal what proportion of the variability in students' situational interest can be explained simply by knowing who the student is and after which class they responded to the ESM survey. The next model will also include students' initial interest and self-concept. Finally, a series of models will be used to understand the individual effects of students' gender, major/non-major status, and self-identification with a racial or ethnic social group—as well as the effects of these individual characteristics when considered collectively. Results will be interpreted in terms of the relationships between the variable of interest and students' situational interest, as indicated by the coefficients, their statistical significance, and their effect sizes in the model.

4.5.2 RQ #2: How do internal (e.g., perceptions of challenge and competence) and external (e.g., the CSEd related activity) contextual factors relate to situational interest?

This question involves understanding how contextual factors—both *internal*, or, students' perceptions of challenge and competence, and *external*, in terms of the CS-related activity undertaken in the class—relate to students' situational interest. Thus, the variables that are being related to situational interest, as well as situational interest itself, are both measured via ESM or at the ESM level. The same general modeling strategy as above is used, again with the lme4 R package (Bates et al., 2015). First, a variance components model accounts for which student and after which class a response came. Next, models for each of the contextual factors—perceptions of challenge, perceptions of competence, and indicators for the activities—will be added to determine the factors' independent effects. Then, the effects of these variables together will be considered. Results will again be interpreted in terms of the coefficients, their statistical significance, and their effect sizes associated with each of the variables.

4.5.3 RQ #3: How does situational interest relate to changes in individual interest in CS?

This question involves determining how situational interest (and its change) relates to changes in students' individual interest. Thus, this question most centrally concerns the process of interest development. Different from the past two analyses, which involved relating student-level characteristics or contextual-level characteristics to students' situational interest, this analysis connects students' situational interest to a student-characteristic—namely, their reports of individual interest. This analysis, then, presents some different (and challenging to consider in an analysis approach) features.

One way to model the data would be to simply calculate the mean, or average, situational interest for each student, and to use that as a variable in an analysis predicting students' end-of-class individual interest. However, this approach is likely to overestimate the effect of students' situational interest because it does not account for the repeated measures nature of the ESM data. Another approach that has been used by researchers in other (non-CSEd and non-educational research) fields is to use a part of the output from the mixed effects model—specifically, the student-specific estimates of students' situational interest—as variables in subsequent analyses. However, this approach also has some limitations, in that it does not account for uncertainty in the predictions of situational interest, again leading to over-confident results (Houslay & Alastair, 2017).

An approach that aims to overcome these limitations involves the use of multivariate, mixed effects models, as described earlier. In particular, these models involve the use of Markov Chain Monte Carlo (MCMC) estimation, whereby students' situational interest as well as their individual interest are both considered outcomes—and so the model is multivariate. Again, the same grouping factors (i.e., levels) of both student and the specific class can be considered. In addition to these considerations, the model also includes students' initial interest and their self-concept. In this way, the analyses associated with this third research question can provide information not only about how situational interest relates to individual interest, but how these relate when accounting for students' level of interest at the beginning of the class. Moreover, this analysis can show how initial interest relates to individual interest when accounting for students' situational interest. Finally, these analyses can acknowledge the role of other individual characteristics—namely, gender, major/non-major status, and self-identification with a racial or ethnic social group.

These analyses will be carried out using the same strategy as for the analyses associated with the prior two research questions, but via the brms R package (Bürkner, 2017), which is more appropriate in this instance because it makes use of MCMC estimation. First, a model with only the grouping factors will be estimated. Then, students' initial interest and self-concept will be included as variables. Next, the remaining student characteristics will be added. In addition, as a final step, the change—from one response to the next—of students' situational interest will be calculated and added to the model. The results will again be interpreted in terms of the model coefficients, their statistical significance, and their effect sizes. To understand the relationship between situational interest (and its change) and individual interest, the correlation between the two variables will be evaluated.

Because these models involve MCMC estimation, there are some additional considerations related to both estimating the models, and interpreting the output. In particular guidelines from Kruschke (2015) for checking the *representativeness* (by checking the burn-in period and the convergence of multiple chains), *accuracy* (by checking the effective sample size and the Monte Carlo standard error (MCSE) for estimates), and *efficiency* of the estimation (by running multiple chains in parallel) will be followed.

4.6 Timeline

The timeline for the project is depicted in Table 1.

Table 1. *Project timeline.*

	Project Year 1				Project Year 2			
	2020 - Q3 (Jul. - Sep.)	2020 - Q4 (Oct. - Dec.)	2021 - Q1 (Jan. - Mar.)	2021 - Q2 (Apr. - Jun.)	2021 - Q3 (Jul. - Sep.)	2021 - Q4 (Sep. - Dec.)	2022 - Q1 (Jan. - Mar.)	2022 - Q2 (Apr. - Jun.)
Attend workshops								
Visit research groups								
Prepare surveys								
Conduct initial survey								
Conduct ESM survey								
Conduct final survey								
Prepare data sets								
Analyze data								
Disseminate findings								

4.6 Creation of deliverables, dissemination of findings and preparation for next steps

After analysis of the data, the next stage of this project will be dedicated to the creation of deliverables, the dissemination of findings, and preparation for next steps. The following deliverables and dissemination efforts will be carried out:

- The creation of a white paper on the analytic approach, including creating a tutorial on its use for other STEM education researchers. This paper will be shared publicly through the Open Science Framework (OSF) repository.
- The preparation of a manuscript for the Special Interest Group on Computer Science Education (SIGCSE) conference on the findings associated with RQ#1 and RQ#2 (i.e., what individual and contextual factors relate to situational interest).
- The preparation of a manuscript for a journal such as *Contemporary Educational Psychology* on the primary findings from this proposed study (i.e., on how situational interests develops into individual interest).

- The sharing of a final, anonymized data set through the OSF repository at the conclusion of this study, for other researchers to use to understand antecedents and outcomes of situational interest in CS.

In addition to these steps, preparation for future work will also be undertaken within the scope of this project. In particular, preparations for subsequent studies of additional CSEd contexts, particularly through the study of an in-development course that is designed explicitly for non-majors to be taken prior to the introductory course that is the focus of this proposed study, using this analytic approach. A part of this proposed study will involve understanding how taking this course (designed explicitly for non-majors) impacts students' interest in CS and achievement in the course. Finally, because this proposed project involves building capacity in STEM education research more broadly, future studies that make use of ESM at the undergraduate and at other levels will also be prepared for.

5. ASSESSMENT OF THE INVESTIGATOR'S EXPERTISE AND EXPERIENCE

The investigator' background is in science education, educational psychology, and educational technology. This confluence of areas has supported the investigator to analyze data using ESM to understand to understand student engagement in science (Rosenberg, 2018; Schmidt, Rosenberg, & Beymer, 2018). The investigator has also conducted prior research in interest development (Blondel et al., advance online publication; Schmidt, Rosenberg, Beymer, Naftzger, & Shumow, 2018).

However, the investigator has very limited experience in developing and carrying out ESM surveys. While the investigator has analyzed data collected via ESM, the investigator has not developed the structure or contents of a survey and has not designed a study (and had to consider how to study the individual characteristics of gender and students' self-reported gender, self-identification with a particular social group, and major/non-major status, as is needed to carry out an ESM study independently. Moreover, the investigator has not had to consider the logistical aspects of carrying out ESM research, including how to time the surveys and how to provide incentives (monetary and non-monetary) for participants.

Another limitation is that the investigator does not have expertise in the multivariate analytic approach necessary for studying the development of interest—and for analyzing ESM data collected in light of other research questions. In particular, the investigator has used mixed effects models but has much less background using them to connect data collected at the situation-level to longer-term outcomes (as proposed for this study). This analytic approach involves using MCMC estimation, which is not a form of analysis commonly taught to educational researchers. Although the investigator has used the approach in several conference presentations, the investigator is not prepared to write a tutorial to advise others on its use. Thus, to address this gap and bolster the investigator's capabilities, the investigator will attend workshops on the MCMC estimation analytic approach.

Finally, the investigator has gaps with respect to mentoring, particularly with respect to mentoring advanced graduate students and post-doctoral scholars. The investigator has not yet mentored a postdoctoral scholar, although doing so is an important professional aim for me. Thus, this project proposal includes support for two years for a postdoctoral scholar. In addition, this proposal includes hourly support for a graduate research assistant., which would provide the investigator an opportunity to develop the capability to mentor a postdoctoral scholar around a focused project that will benefit them in terms of experiences and training as well as scholarly products such as conference presentations and publications. In addition, because a graduate student will be involved, the investigator would have the opportunity to establish the foundation for the investigator's future research group.

Addressing these gaps (with respect to ESM, the particular analytic approach, and mentoring) will help the investigator to be better positioned to carry out CSEd and STEM education research that can help to answer questions and to solve problems of interest to others in the investigator's department, University, and state. Moreover, addressing these gaps will provide the investigator with an opportunity to bridge gaps between related fields (i.e., CSEd and STEM education and CSEd and the learning sciences and educational psychology) that have, historically, not had as much overlap as may be beneficial (Wilson, 2002; Lishinski et al., 2017). Doing so will prepare the investigator to carry out the kind of transformative STEM education research that the NSF is seeking to support.

6. PROFESSIONAL DEVELOPMENT PLAN AND RATIONALE FOR SELECTION OF THE ADVISORY BOARD

While the investigator has experience in STEM education, this project is associated with a professional development plan that builds on the investigator's experiences to develop expertise in a methodological approach that is not-yet-used in STEM education, ESM. The professional development plan with respect to ESM involves three primary tenets: observing two ESM research groups, attending a workshop on ESM, and reading and discussing texts on a targeted reading list guided by my project mentor. One of the two ESM research groups is associated with my project mentor Dr. Jennifer Schmidt; observing and learning from the activities of this group will help the investigator to understand how thoughtfully study students' individual characteristics such as students' self-reported gender, self-identification with a particular social group, and major/non-major status. The other research group will help the investigator to develop expertise in studying learning across contexts. The investigator will attend a workshop on ESM—using ESM as well as analyzing data from it. Finally, the investigator will construct with his mentors to develop a targeted reading list on ESM methods. These readings will inform how the investigator designs ESM items and carries out the pilot study using ESM.

In addition, to enhance the investigator's capacity to be involved in research with students who report being from groups who are under-represented in the domain, the investigator will attend meetings sponsored by the cross-campus Diversity Collaborative in Education group, which both sponsors events and seminars and also highlights other events and seminars of relevance across campus. To be prepared to analyze the ESM data, the investigator will also attend a workshop on MCMC methods. Finally, the investigator will attend the meetings of a CSEd research group to understand which sources of situational interest may be most relevant to the pilot study using ESM.

The proposed project would be supported by two mentors (who are also advisory board members) and two advisory board members consisting an expert in the use of an experience sampling method and gender in STEM, CSEd researchers, the chair of the CS department at the investigator's institution. In particular, the following mentors and advisors will help to address the aforementioned gaps in the investigator's experience and expertise:

- Dr. **Chrystalla Mouza** is a Distinguished Professor of Teacher Education, specializing in educational technology, and director of the School of Education at the University of Delaware. Dr. Mouza will serve as an advisory board member for this project. She has expertise in the learning sciences, including teacher learning, applications of technology in K-12 classrooms, and teaching and learning outcomes in ubiquitous and mobile computing environments.

- Dr. **Gregory Peterson** is the Professor and Chair of Electrical Engineering and Computer Science at the University of Tennessee, Knoxville. Dr. Peterson has expertise in computer science as well as designing introductory courses for CS newcomers. Dr. Peterson will serve as an advisory board member for this project. He will advise the PI on all aspects of the project, particularly those related to the computer science course and the logistics of carrying out research in the undergraduate CS course context.

- Dr. **Jennifer Schmidt** is an Associate Professor of Educational Psychology at Michigan State University. Dr. Schmidt will serve as a co-mentor and advisory board member for all aspects of the development and implementation of the project as well as the implementation of the professional development plan. Dr. Schmidt has expertise in adolescent motivation and engagement in learning contexts, both inside and outside of school. Her work informs and is informed by, scholarship on human motivational processes as well as work on adolescent development, gender educational intervention, and educational environments. Dr. Schmidt uses the Experience Sampling Method (ESM) and has written one of the leading handbooks on the use of the ESM approach.

- Dr. **Aman Yadav** is a Professor in the College of Education and the Director of the Masters of Arts in Educational Technology program at Michigan State University. Dr. Yadav will serve as a co-mentor and advisory board member for this project. In addition to a Ph.D. in Educational Psychology and Educational Technology, Dr. Yadav has Bachelor's and Master's in Electrical Engineering. Dr. Yadav's research focuses on computational thinking, computer science education, and problem-based learning. He has carried out studies using a daily diary approach to study students' experiences in CSEd contexts.

The main mechanism to assess the success of the proposed project will be the input of the advisory board. This board will help assess the success of the project as well as the professional development plan. The investigator will remain in contact with the advisory board via meetings as well as communication about all aspects of the project, from its design through its implementation. Success will be determined based upon producing a white paper, final dataset to share, and annual reports. Each of these products each of the products will be sent to mentors and advisory board members prior to being disseminated more widely.

7. RESULTS OF PRIOR NSF SUPPORT

Dr. **Joshua Rosenberg** is serving as a Senior Consulting Investigator and served as a significant contributor to the method for the Profiles of Science Engagement (PSE) study, funded through the EHR Core Research program (DRL 1661064; $499,927; 2017-2020). *Intellectual merit*. This study advances knowledge in STEM education by identifying instructional contexts that foster optimal student engagement and by examining whether adolescent students' engagement profiles in science vary systematically by gender, race/ethnicity, and their interaction. The project makes use of an innovative person-oriented analytic approach adapted from its use in developmental research in order to understand student engagement in-context and over time. *Broader impacts*. This work is revealing how student engagement varies across and is related to features of the science learning context, achievement, and persistence-related outcomes. This project would also develop statistical software enabling other researchers to carry out similar person-oriented analyses, as well as develop a teacher guide for recognizing and responding to student engagement in science. *Selected publications and products*. The statistical software was developed and made freely available for this project and was documented in the *Journal of Open Source Software* (Rosenberg, Beymer, Anderson, & Schmidt, 2018). Preliminary findings have presented at the *American Educational Research Association Annual Meeting* (Beymer, Schell, Alberts, Rosenberg, & Schmidt, 2019; Rosenberg, Beymer, & Schmidt, 2018; Rosenberg, Beymer, Houslay, & Schmidt, 2019).

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Budget Justification

A. Senior Personnel

The principal investigator for this project is Dr. Joshua Rosenberg. Dr. Joshua Rosenberg is requesting 1.5 academic months and .5 summer months for each year of the two-year project. He will oversee all of the aspects of the project, including data collect and data analysis, and will complete a professional development program including consulting with the advisory board, participating in conferences and computer science education research groups. Total salary requested is $33,455 fringe calculated at 41.3% for the academic year and 17.7% for summer.

B. Other Personnel

We are requesting a 12-month postdoctoral fellow for each year of the two-year project. The postdoctoral fellow will have an earned doctorate in computer science, computer science education, or a related field (i.e., STEM education or the learning sciences). This postdoctoral fellow will be involved in the data collection, data analysis, and dissemination of research findings. Total salary requested in year 1 is $50,000 (with a 3% increase in year 2) and fringe calculated at 33%.

A total of $3,750 is requested for hourly support for one graduate student research worker ($15/hour) for 150 hours in year 1 and for 100 hours in year 2. Fringe is calculated at 8%.

E. Travel

For the duration of the project, travel is requested at $10,983.

$1,825 is requested for travel to attend a research methods conference during year 1 that includes workshops on the ESM in Whitefish, Montana and are estimated as follows:
Registration = $400
Flights = $500
Hotel x 3 days at $200/night = $600
Per Diem at $75/day for three days = $225
Ground Transportation $50 per trip x 2 trips = $100

$3,450 is requested for travel to attend a computer science education research group in year one for two days and to attend two ESM research groups also in year one for two days. Locations are unknown and estimated as follows:
Flights/Transportation = $1,200 ($400 x 3 flights)
Hotel x 6 days at $200/night = $1,200
Per Diem at $75/day x 10 days = $750
Ground Transportation $30 per trip x 10 trips = $300

$2,200 is requested to attend a workshop in year 2 on the use of the Stan software/MCMC estimation. Conference location is unknown and estimated as follows:
Registration = $900
Flights = $500
Hotel x 2 days at $200/night = $400
Per Diem at $75/day = $225
Ground Transportation $50 per trip x 3.5 trips = $175

$3,508 is requested for travel to attend the 2-day National conference each year. Conference location is estimated on Washington, DC rates:
Registration = $500
Flights = $500

Hotel x 2 days at $251/night = $502
Per Diem at $76/day = $152
Ground Transportation $50 per trip x 2 trips = $100

G. Other Direct Costs

1. Materials and Supplies

$1,400 is requested for use of the Survey Signal software for carrying out the Experience Sampling Method survey. This cost is estimated at $20 per participant for 70 participants in year 1 for a total cost of $1,400.

$119 for books for two directed readings on ESM.

3. Other

Honorarium for mentors

Two mentors, one with expertise in computer science education and another with expertise in the experience sampling method, will provide advice about both the development and the implementation of the project as well how the professional development plan is carried out. $3,000 per year is requested to pay each mentor.

Honorarium for Advisory Board Members

Three advisory board members will provide advice throughout the development and implementation of the project. $2,000 per year is requested to pay each advisory board member.

6. Other

Honorarium for participants

175 participants will be provided with a $50 gift card in year 1 for a total expense of $8,750.

H. Total Direct Costs--$229,595

I. Total Indirect Costs--$117,093

UT has used its federally negotiated rate for on-campus research of 51%.

J. Total Costs: $346,688

July 15, 2019

Dear Dr. Rosenberg,

Listed below are concerns raised by the panel that reviewed the proposal (ECR: BCSER-1937700) you submitted to the ECR:BCSER program. Please respond to the program concerns in no more than ***3 pages.*** The response must be submitted to me by close of business on **July 16, 2019.** Your responses may be submitted via an email attachment.

Thank you.

Celeste

Program Concerns Requiring Clarification:

1. The primary goal of the ECR: BCSER Individual Investigator Development (IID) in STEM education research is to facilitate the acquisition of education research expertise that will position you to successfully conceive and execute fundamental research with the potential to meaningfully advance current knowledge in one of ECR's research domains (learning and learning environments, broadening participation, and workforce development). As such, it is not clear how your proposed individual professional development plan (IDP) will achieve that goal. Therefore, you will need to:
    a. Explain how your IDP might be redesigned to include activities that will significantly enhance your knowledge and skills in using ESM to conduct fundamental research; and
    b. Identify critical factors necessary to enhance your methodological knowledge in ESM, provide specific details about what activities you will engage in to acquire the advance knowledge in ESM, and include specific details about the role mentors and the advisory board will play in the effort.

2. There was limited information in the proposal about how the project will address methodological challenges which arise from ESM and longitudinal research regarding response rates and attrition. Specifically:
    a. How much missing data are expected and how will this situation be accounted for during data analysis?
    b. What incentives will be offered for paying participants, as this timing has implications for response rates?
    c. Will there be adequate variations in instructional design and types of students in an undergraduate introductory computer science course to support an EMS study?

Budget Concerns Requiring Clarification:

1. Successfully addressing panel concerns listed above will require changes to the budget. Please revise the budget Forms 1030 and narrative to match the revised IDP accordingly.
2. Justify the request for more than 2 months of support each year as PI of the project.

PLEASE NOTE: I can be reached at 703 292-5186 on Monday, July 15, 2019. Please email me for a time to discuss this matter. This is a one-time opportunity to provide clarifying information.

Responses to questions for clarification: Understanding the development of interest in computer science: An experience sampling approach (ECR: BCSER)

Response to Question 1A.

I have re-designed my Individual Development Plan (IDP) to focus on activities that will significantly enhance my knowledge and skills in using the Experience Sampling Method (ESM) to conduct fundamental research. Specifically, I have made changes to my IDP as detailed below and as reflected in my revised narrative (particularly section 5, on my past experience, and 6, on my IDP).

- *I added attending two ESM research groups*. I have received confirmation from Dr. Schmidt at Michigan State University to attend meetings for her M-PLANS project (NSF Award, 1813047). I also will attend virtual meetings for the MPLANS project, particularly those related to developing the ESM instruments to be used. I have also received confirmation from Dr. Xie at Ohio State University to attend the meetings of his research group, which uses ESM to study learning across contexts. My involvement, which will involve observing, asking questions, and receiving feedback on my study design, will help me to develop an understanding of best practices in ESM research and how to navigate issues and dilemmas that arise in the course of doing ESM research. More particularly, involvement in Dr. Schmidt and Dr. Xie's research groups will help me to develop expertise in studying students' individual characteristics and learning across contexts, both of which I consider to be critical factors to help me grow methodologically.

- *I added attending a workshop on ESM.* This workshop would be a part of the *Developmental Methods* conference and would be hosted by Drs. Bolger and Laurenceau, who regularly present on ESM, including at stand-alone workshops and in conference workshops. A benefit of attending their workshop at this conference is that it is included in the cost of attending the workshop and that I may present and benefit from other's work using ESM, as well.

- *I added a targeted reading list related to ESM methods*. I will develop this list with the support of my mentor, Dr. Jennifer Schmidt. I added books by both Schmidt as well as the organizers of the ESM and daily diary methods workshop, Bolger and Laurenceau (2013) as materials that will be one part of this list. These readings will inform how I design and carry out the ESM survey.

These changes will position me to significantly enhance my knowledge and skills in using ESM to carry out fundamental research, particularly with respect to structuring ESM surveys, studying individual characteristics and variability, and carefully considering the logistics of timing and incentives. These lessons, then, can be applied later to the study of learning and learning environments in a range of STEM education settings—including settings in which it has not yet been widely used, such as in the focus on CS education in my pilot study. In light of these proposed changes, I proposed to move the data collection from the Fall, 2020 semester, to the Spring, 2021 semester. This will allow me greater time to anticipate possible issues related to the ESM data collection and to develop a stronger data collection plan.

While I re-designed by IID, I retained some aspects of it as it was originally planned. In particular, I retained the workshop on MCMC analytic techniques, as this will be imperative to how I analyze the ESM data (and is important for the analysis of such data). However, I will use my time with the organizers to ask questions specific to ESM. In addition, I will still include travel to one CSEd research group, although, I will use this time to understand which sources of situational interest may be most relevant to the pilot study using ESM. Finally, I retained attending the cross-campus Diversity Collective meetings to deepen my understanding of the barriers students from groups who are under-represented in CS may face—and to inform how I plan and carry out ESM.

<u>Response to Question 1B.</u>

The following four critical factors will help me to grow methodologically over the next two years, starting with my specific skills (and gaps in them) at the moment and how I must grow through selected activities and my mentor's/advisor's involvement. For each of the four factors, I only note my mentor's/advisor's roles when they are not already referred to in the description of the activities.

Critical Factors	*Activities*	*Mentor's/Advisor's Roles*
1. How to study students' individual characteristics	Attend Dr. Schmidt and colleagues' ESM research group to ask questions and receive targeted feedback on how I study students' individual characteristics (self-reported gender, self-identification with a particular social group, and major/non-major status)	Drs. Schmidt and Mouza: Identify readings; provide input on the study design
2. How to construct ESM surveys	Attend Dr. Schmidt and Dr. Xie' ESM research groups to observe best practices for ESM survey design and to ask questions and received targeted feedback to develop ESM items as well as a system for signaling students and receiving their responses Attend a workshop on ESM to learn contemporary approaches to ESM survey construction	Drs. Schmidt and Yadav: Identify readings, provide input on ESM items and on the SurveySignal tool
3. How to study variation in students' experiences	Attend Dr. Xie's ESM research group to ask questions and receive targeted feedback on how to explore the experiences of students as they prepare and study for class (rather than only during the class) Attend a workshop to learn how ESM can be used to study experiences in a wider range of settings	Drs. Schmidt and Yadav: Identify readings, provide input on the ESM data collection plan as well as how distinct instructional will be identified/coded.
4. How to structure/time ESM studies	Attend a workshop on ESM to learn how to structure an ESM study to maximize student participation (and to minimize disruption for students and instructors)	Drs. Schmidt and Peterson: Provide input on the structure/timing of ESM surveys.

Response to Question 2A.

Missing data is an important issue for ESM research. In the pilot study, the use of MCMC estimation will accommodate missing ESM data because the technique, like multi-level models, can accommodate missing or unbalanced responses that are "grouped" within students like they are for ESM. Even still, and related to Critical Factor #4 above, I will take steps to minimize the amount of missing data. However, missing pre- or post-survey data will present greater challenges, and so plan to accommodate the missing data using other strategies. For instance, I plan to use multiple imputation for missing pre- or post-survey data (and to not include students missing both pre- and post-surveys). I will also plan to learn more about this issue in the workshops on MCMC I attend.

Response to Question 2B.

I agree that it is important to carefully consider the incentives plan, both its monetary as well as potential non-monetary aspects. I plan to pay participants $30. I plan to pay them $5 at the beginning and $5 at the end. In order to ensure a high ESM response rate, students will be paid $5 if they respond to at least one ESM signal, $10 if they respond to three, $15 if they respond to four-15, and $20 if they respond to more than $15. This will also be something that I will address with my mentor, Dr. Schmidt, and at the research group and workshops I attend, were any changes to be possible to make, in the first quarter of the project.

Response to Question 2C.

How much variability will be present in a typical, introductory CS class is an important consideration. The course is presently being re-designed to be more 'active' (according to the Department Chair) and to involve a greater range of instructional activities for students. In addition, the course does include non-majors. Still, I think this is a very important consideration, and a strategy I will use will involve asking participants during Week 4 to select a time when they are working on coursework outside of the course to be surveyed about their studying. This will provide additional measures with perhaps greater variability. In addition, I will develop skills related to measuring variability both in- and out-of-class through the activities/guidance included in my IDP.

Response to Budget Concern 1

I made changes to the budget in light of the revised IDP, as reflected in the new budget justification.

Response to Budget Concern 2

If all pending NSF submissions are selected for award, my summer and academic year percent effort will exceed 2 months of support in each of this project's two years. This is necessary given the demands of the Individual Investigator Development Plan, my involvement as the Principal Investigator for the pilot study and mentoring a post-doctoral scholar and graduate students. Accordingly, I respectfully request an exception to the 2-month NSF salary support limitation in the event that all outstanding NSF submissions are awarded. I will be happy to provide additional information upon request.

Postdoctoral Mentoring Plan

One postdoctoral researcher will be employed full time for 24 (two years) months to plan the proposed study, collect and analyze data, and interpret and share findings. Dr. Rosenberg will work with the postdoc to develop an Individual Development Plan that describes the postdoc's research and career goals, specific activities for achieving those goals, and mutual expectations for an effective mentoring relationship. The activities listed below are designed to support the postdoc's goals and provide a foundation for future success in computer science education and/or STEM education research. The PI and postdoc will establish a regular meeting schedule to discuss the postdoc's progress on stated goals, status of the research, and overall project management. The PI will conduct a biannual performance review to assess progress and provide feedback.

Research Procedures

- The PI will provide an orientation to the laboratory that will include a discussion of (a) level of independence, (b) interaction with coworkers, (c) productivity goals, (d) work habits and protecting the confidentiality and privacy of participants in the study and (e) documentation of the experience sampling and survey research methodologies
- The postdoc will receive training in Responsible Conduct of Research and human subjects research through online and in-person trainings available through the Office of Research and Engagement, University Libraries, and research integrity/compliance webinars.

Preparation of Grant Proposals

- The postdoc will receive training in identifying appropriate funding mechanisms, crafting a competitive research proposal, and developing a career research plan through the Office of Research and Engagement proposal development workshop series. The PI will also involve the postdoc in writing grant proposals and provide recommendations for a long-term funding plan that identifies which opportunities are appropriate for different career stages.

Publications and Presentations

- The PI will provide guidance on the publication process, including organizing and writing the manuscript, deciding where to submit, communicating with journal editors, and responding to peer reviews. One resource will be the University Library's Publishing Toolkit website.
- The postdoc will participate in the PI's weekly research group meetings in which participants present their research and receive feedback from the group. The feedback will emphasize the development of strong communication and presentation skills.

Teaching and Mentoring Skills

- The PI will provide guidance on managing and preparing a research team, including graduate and undergraduate students.
- The postdoc will have the opportunity, depending on interest and past experiences, to teach or to co-teach a class. The PI will advise on best teaching practices to motivate students, and develop and assess learning goals.

- If the postdoc is involved in teaching, the PI will encourage use of the University's Teaching and Learning Center. Resources are also available through the University's membership in the Center for the Integration of Research, Teaching, and Learning Network.

Success of this mentoring plan will be assessed by tracking the progress of the postdoctoral fellow through his/her Individual Development Plan, assessing the postdoc's satisfaction with the mentoring plan, and revising the IDP as needed in response to changing goals or new areas needing improvement.

University of Tennessee, Knoxville – Facilities and Other Resources

Computer: All personnel involved in this project have access to the University of Tennessee, Knoxville's state of the art computer facilities, offering high-speed Internet access as well as access to the latest technological developments in academic computing. This includes access to all necessary data processing and analysis software. Technical support and training opportunities are available, if needed.

Office: All personnel involved in this project will have offices that are located in close proximity to each other, allowing ease in scheduling and meeting. Conference rooms are available to be scheduled for larger research group meetings as well as well as for advisory board meetings.

Other Resources: The Advanced Computing Facility (ACF) provides access to high-performance computing resources, as needed, to researchers at the University of Tennessee, Knoxville. The ACF provides support for sensitive applications as well as fast data access and ample storage for sensitive data.

Other: The University of Tennessee, Knoxville, is a large research institution with more than 22,000 undergraduate and 6,000 graduate students. The University of Tennessee, Knoxville's library collection includes more than million journals and most journals are available via online databases.

Sources and the development of interest in computer science: A person-in-context approach and analytic technique

Roles and responsibilities

Specify the roles and responsibilities of all parties with respect to the DMP activities.

The PI will be involved in the data collection, management, analysis, and curation for storage. The post-doctoral scholar will also be involved in these processes: data collection, management, analysis, and curation for storage. The graduate and undergraduate students will be involved in the data collection and data management.

Types of data or products

Specify the types of data or products that will be generated (e.g., test scores, survey responses, images, data tables, video or audio data, sftware, curricular or exhibit materials).

Two types of survey data will be generated: data from experience sampling method (ESM) surveys and data from longer, traditional surveys. In addition, demographic data from participating students will be collected.

Data storage, preservation, and sharing

Specify how data or products are to be stored, preserved, and shared.

The data will be collected with identifiers but these identifiers will be removed prior to analyzing and curating the data for storage. This data with identifiers removed will be saved on the Open Science Framework, a secure data repository which provides access via a website and an Application Programming Interface to access the data.

Restrictions on data or product storage, access, preservation, or sharing

Specify any restrictions on data or product storage, access, preservation, or sharing

The data will only be shared with all identifers removed. Participants will be informed that the data may be shared for peer-review or upon request by other researchers.

Data formats

Specify what data formats will be used (e.g., XML files, websites, image files, data tables, software code, text documents, physical materials).

The data will be stored and used in comma separated value (CSV) formats.

Period of data retention

Specify how long access to data and products, and sharing of data or products, will be maintained after the life of the project, and how any associated costs will be covered and by whom.

Data with identifiers will be kept for one year after the conclusion of the study.

Third-party preservation

If data or products are to be preserved by a third party, please refer to their preservation plans if available.

The data without identifiers will be retained for 50 or more years, as the Open Science Framework has committed to.

Additional possible data management requirements

More stringent data management requirements may be specified in particular NSF solicitations or result from local policies and best practices at the PI’s home institution. Additional requirements will be specified in the program solicitation and award conditions. Principal Investigators to be supported by such programs must discuss how they will meet these additional requirements in their Data Management Plans.

Question not answered.