Interest Development Theory in Computing Education: A Framework and Toolkit for Researchers and Designers

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Computing is rapidly becoming a critical literacy for succeeding in an increasingly technological world. While the proliferation of programs dedicated to broadening participation in computing increases access, computing education research can benefit from more directly drawing on current interest development theory to improve interventions that increase the desire to participate and persist in computing. In this article, we present an overview of current interest development theory and provide guidance to computing education researchers on ways to ground their conceptualization and measurement of interest in contemporary theory and inform ways of interweaving interest theory throughout intervention or curriculum design. The central contribution of this work is presenting the Integrated Interest Development for Computing Education Framework. This framework is organized around three central dimensions of interest: value, knowledge, and belonging. For each of these dimensions, the framework presents key factors that link the dimension to strategies that can be employed in computing education contexts to help develop interest. The article also describes methods of measuring interest in computing that are consistent with interest development theory, and provides examples and resources for validated measures of interest. We conclude with a discussion of the implications and potential for improving the conceptualization and measurement of interest development in computing education and future work needed to advance an understanding of how interest in computing develops that can lead to improving the design of computing educational programs to support interest development.

CCS Concepts: • **Applied Computing → Education;**

Additional Key Words and Phrases: Interest development, broadening participation, theory in computing education

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1 INTRODUCTION

Promoting student interest in computing is of major importance, as a foundational understanding of computational ideas is important for youth to fully participate in an increasingly computational world. Participation in computing learning opportunities has increased significantly over the past

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few decades, but many barriers, including stereotypes about the field and a lack of access to resources and learning opportunities, continue to impede many youths from developing the interest needed to engage in these opportunities. This need to increase opportunities and interest in computing has led to an influx of formal and informal programs that provide access to opportunities to participate in computing education, and many programs have specifically sought to increase opportunities for historically excluded groups such as women and students who identify as Black, Indigenous, or people of color. While this proliferation of programs has made strides towards increasing access to opportunities, it is crucial to also bolster long-lasting interest in computing for students to engage in those opportunities [124]. While much of the focus to date has been on working towards the goal of increasing participation through access, with this work, we shift from emphasizing access towards efforts to *make interest a central design consideration for computational learning opportunities to increase and broaden participation in computing*. To support integrating interest development theory into research and practice in computing education, we present the Integrated Interest Development for Computing Education Framework, presented in Figure 1.

While empirical studies examining interest in computing are proliferating, relatively little work has sought to connect these efforts with contemporary theories on interest development. Towards that end, a recent report by the National Academies of Science made a significant step in illustrating how authentic learning environments in computing can facilitate interest and competencies in computing [103]. In the report, the authors urge researchers to reevaluate approaches to learning environment design to better reflect the lived experiences and values of a wider variety of learners. The theoretical framework defined in this work is designed to complement and build on the National Academies report to provide a useful tool for computing education researchers and practitioners in creating and evaluating computing opportunities that positively influence learner interest in computing. The Integrated Interest Development for Computing Education Framework is organized around three focal *dimensions* drawn from current interest development theory: Value, Knowledge, and Belonging (Figure 1, center ring). Each dimension of the framework is expanded to highlight *key factors* (Figure 1, middle ring) that represent unique aspects and approaches from the interest development literature to foster interest development. Those key factors in the framework are then linked to specific curricular design strategies and examples to illustrate concrete approaches that incorporate the key factors of interest development into computing education contexts (Figure 1, outer ring).

The structure of this article follows the structure of the Integrated Interest Development for Computing Education Framework, beginning at the center and working outward. We begin with a review of current interest development theory, organized around three focal dimensions: Value, Knowledge, and Belonging. We continue with key factors that build on these focal dimensions and demonstrate how each dimension is instantiated in the context of computing education with examples of pedagogical and design strategies drawn from the computing education research literature. We then discuss how this framework informs ways of measuring interest in computing education contexts and conclude with a larger discussion of the implications and contributions of this work.

2 INTEREST DEVELOPMENT THEORY

2.1 Situational and Individual Interest

Interest development theory defines interest as a developmental motivational variable that can refer to both *situational interest*, a psychological state of heightened attention and focus in relation to some content or activity, or *individual interest*, a relatively stable disposition to reengage with that content or activity [123]. This perspective takes a developmental approach to the construct

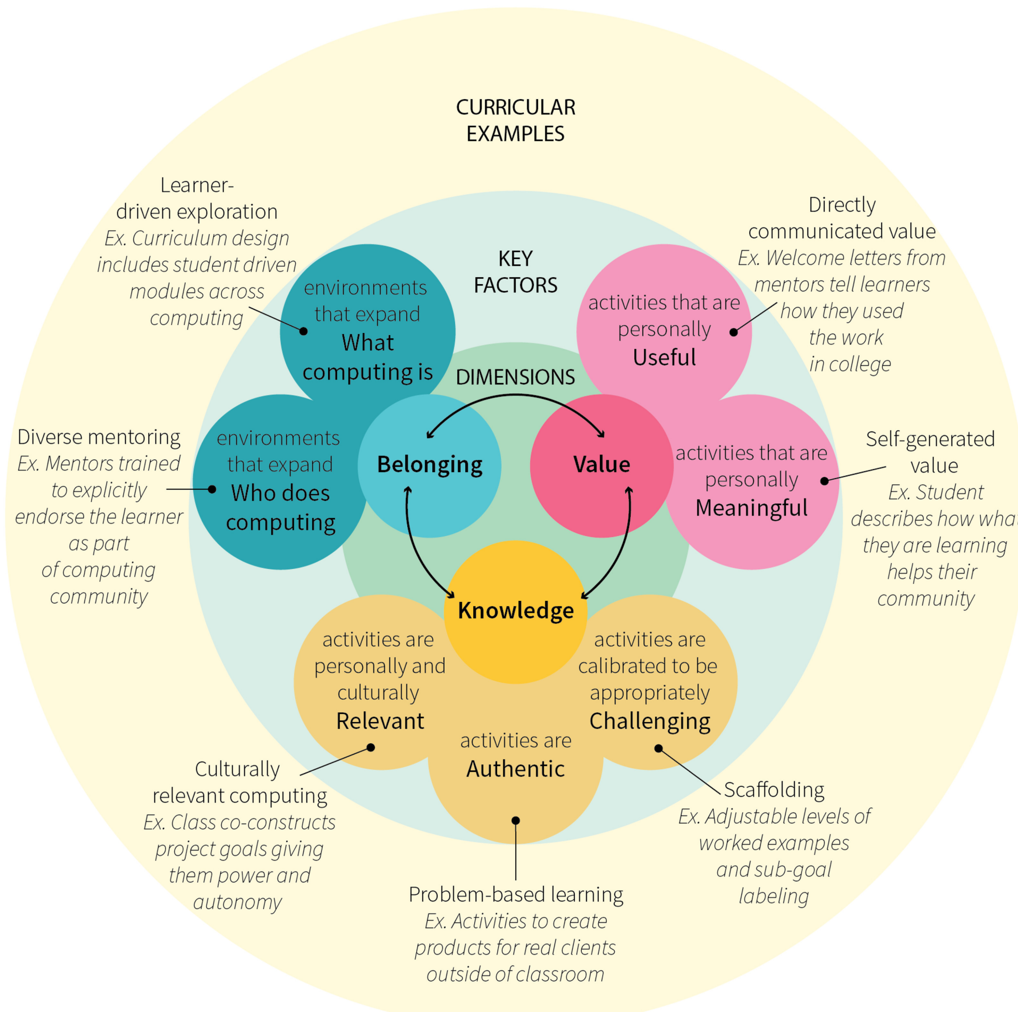

Fig. 1. The integrated interest development for computing education framework, including dimensions of interest development (center ring), key factors that contribute to each dimension (middle center), and curricular examples to enact key factors (outer ring). ©Authors.

of interest that goes beyond seeing academic interest as a general characteristic or in terms of career or vocational interest as an occupational choice. Evidence from neuroscientific research has demonstrated a link between interest and the reward-seeking and novelty-seeking circuitry in our brains, where rewards, expectations of rewards, learning, and novel encounters all increase an individual's attention, reaction times, and performance [55]. These findings help explain the mechanisms at play in interest and in developing interest, where individual interest may be built in part on prior experiences that have fulfilled the reward and novelty-seeking motivations that drive behavior.

Situational interest is often distinguished between fleeting moments of interest that catch or *trigger* interest and longer-lasting situational interest that is held or *maintained* over time. These distinctions can be useful in how we interpret the strength and longevity of situational interest that is spawned in the moment. Triggered situational interest can be fleeting and can be activated by novelty, challenge, surprise, group or problem-based activities, meaningfulness, and relevance [120]. Although there is some argument that maintained situational interest is better conceptualized as multiple re-activations of triggered interest [130], situational interest persists when an individual perceives the content or activity as important or meaningful [56].

Individual interest can be distinguished between *emerging* individual interest, which may diminish if the individual does not find sufficient resources, environmental supports, and positive feedback in relation to the activity; and *well-established* individual interest, which is uniquely resilient and stable over time. Both situational and individual interest are considered motivational variables, as they impact motivated behavioral actions and are distinct but related to other motivation-related variables such as enjoyment, attitudes, curiosity, achievement goals, intrinsic motivation, and self-efficacy [57, 98, 117]. Of particular note is the need to resist conflating enjoyment or attitudes with interest, as interest is one of many potential factors that can lead to enjoying an activity and comprises one of several factors that may constitute attitudes towards content [77].

To develop interest in an academic content area such as computing, educational researchers often aim to build individual interest, where learners persist with and seek out additional opportunities to engage with content in the long-term that further develops their interest and benefits learning. Individual interest is thought to develop across multiple instances of positive situational interest, particularly where situational interest is maintained over time [56]. Much of the interest development literature has recognized positive affect as an early contributor to triggering situational interest. However, finding **value** and increasing **knowledge** in the content are two key dimensions of interest that maintain situational interest and build towards individual interest [122]. A third dimension of interest development, developing a sense of **belonging** and connection to content, has emerged more recently, as interest researchers have applied a socio-cultural lens to understanding interest and motivation [6, 13]. Importantly, increases in any one of these dimensions can also be related to increases in the other dimensions. So, gaining knowledge will promote perceptions of value and feelings of belonging, if that knowledge helps the learner see why it is valuable and helps them more strongly identify with the communities and activities associated with that content. Therefore, while we outline each dimension in Section 3, our exploration of key factors contributing to interest, in Section 4, emphasizes building learning opportunities that support each dimension in ways that complement the others.

2.2 Social and Cultural Influence on Interest

Before turning to the three dimensions of interest development in the framework, it is important to discuss the role of socio-cultural factors in influencing interest. A socio-cultural or situative approach has garnered recent attention in interest development research that highlights the interaction between individual-level processes of interest development with social feedback and the surrounding cultural context that activities take place in [13, 112]. The implications of socio-cultural factors manifest in two directions: the environment's influence on the learner, where inclusive and supportive spaces can build feelings of knowledge, value, and belonging; and how the learner interprets the environment, by bringing to bear their history, perspective, and background in identifying and engaging with the values, practices, and community associated with the content [7]. Therefore, interest development researchers expand their lens for examining and conceptualizing interest by incorporating an interaction between the learner and the environmental factors and socio-cultural backgrounds of learners to understand their relationship with and interest in content [102].

Learners inherently create meaning, assign and assess value, and interpret and infer connections to what they experience, and each of these processes is indelibly linked and shaped by socio-cultural feedback and context. Learners are building a concept of their own self-identity within these contexts that strongly shape their interest, in part by defining their roles and opportunities for participation [63]. It is important to acknowledge that many of the existing structures and institutions of formal education, especially around computing, restrict who has the power to define and evaluate what constitutes knowledge and what is meaningful and valuable in content areas and disciplines like computing [41]. This leads to institutional bias against those typically excluded from computing. For example, the local and cultural context of what counts as competence in computing can influence a learner's assessment of their own knowledge and competence and diminish and exclude learners who do not conform to competence as defined by formal institutions. In some countries, such as the United States, United Kingdom, and Sweden, women's knowledge and contributions in computing have been ignored, erased, or diminished and has had negative implications on women's interest in computing, but women participate in computing at a high rate in other countries, such as Saudi Arabia, where families and government supports for their efforts foster interest [3]. Similar exclusion has impacted learners around the globe who identify as Black, Indigenous, or people of color [136]. To break this cycle of exclusion, learners may be more likely to believe in their own competence and knowledge in an environment that embraces multiple ways of knowing and practicing computing and that gives learners the power to define how their competence is measured, than if they were in an environment that assesses knowledge through standardized testing or normative comparisons to standards. This effect also holds for feelings of value and belonging, where the discourse of participation and feedback from others in the learning environment, family, community leaders, or other peers can radically shape what the learner believes is valued in the field of computing, what they see as valuable uses of computing, or whether they belong amongst those who engage in computing activity. By shaping their participation and providing external cues about value and belonging, the socio-cultural context shapes the learner's own perception of whether computing as a discipline is congruent with their values and with their beliefs about where they belong [34]. It is important that as a field, computing education seeks to develop interest in computing, not through enculturation into existing rigid concepts of computing, but through expanding the norms, discourse, and practices that are recognized as computing.

Beyond the socio-cultural context shaping the learner's perspective about knowledge, value, and belonging, we can also consider how a learner's experiences across multiple spaces with multiple interests influence their interest in content [1, 8]. A lines-of-practice perspective considers interest as motivated behavior that results in pursuing activities that are congruent with multiple levels of an individual's existing and emerging interests, rather than a simple relationship between a learner and specified content [5]. This perspective on interest highlights the limitations of splitting courses and programs along subject area lines, as these rigid definitions do not readily engage the multiple lines of practice that form interest [144]. From this perspective, it is important to see how learners continually look to shape their learning to match their interests, perspectives, and experiences, and incongruities within their experiences can reduce feelings of value and belonging and diminish a desire to learn the content.

3 THE THREE DIMENSIONS OF INTEREST DEVELOPMENT

Interest development theory considers interest as a complex and multidimensional variable that can be influenced through multiple supports and environmental factors [45]. This complexity leads to unique manifestations of interest [37] and subsequently multiple pathways for developing interest and persistence in content, such as computing or **science, technology, engineering, and math (STEM)** [2]. Therefore, in designing for individual interest development, it is critical to take a multidimensional approach that focuses on triggering and maintaining situational interest to

build knowledge, value, and belonging in relation to the content [129]. In this section, we focus on knowledge, value, and belonging as three major dimensions of interest that lie at the heart of the Integrated Interest Development for Computing Education Framework.

3.1 Knowledge

Developing knowledge within a content area is thought to be reciprocally related to developing interest in that content [42, 122]. That is, acquiring knowledge of a content area promotes interest, through repeated experiences of situational interest, and that individual interest inspires the acquisition of more knowledge. The knowledge-deprivation hypothesis explains how acquiring knowledge activates situational interest when a learner is confronted with a problem and realizes a gap between what they know and what is needed to solve the problem [129]. This gap motivates us to seek information to solve the problem, and successfully acquiring the needed knowledge satisfies an innate drive to learn. These successes may encourage future engagement or seeking information when confronted with similar problems or problems with increasing complexity and serve to build a foundation for seeking re-engagement with content.

Existing individual interest is also thought to spur seeking new knowledge, where interest as an individual factor influences activation of situational interest in an activity. Here, existing interest primes learners to see the value and meaning in a related activity, and the subsequent activation of situational interest further strengthens individual interest. This effect can be true for learners with high individual interest who understand and voluntarily seek connections between their existing knowledge and new learning opportunities [77]. The effect can also be true for those with lower interest in the content who are given supports to see connections between their existing interests and the content or related content [123]. In short, an emerging or well-developed interest in content is accompanied by a desire to build knowledge of that content that drives the learner to begin their own projects, seek mentors, teach others, and enroll in elective learning opportunities in and outside of schools [33].

3.2 Value

The perception of value represents a second critical dimension to the development of interest [50]. The perception of value in relation to content is thought to build over time and, like knowledge, can be reciprocally related to interest—increasing value generates interest and increasing interest generates value. It is believed that the perception of value increases interest by creating mental connections between the person's perception of themselves and the content, which in turn engages the emotional and reward-seeking systems in the brain [52, 58]. Much of the interest development field's understanding of promoting value for content derives from the literature on expectancy-value, where both the value for the activity, operationalized as usefulness and importance, and the expectation that one can accomplish the activity are interrelated in determining motivated behavior [149, 150]. This relationship may also explain part of the relationship between increasing knowledge and value, as higher levels of knowledge positively contribute to ability beliefs and expectancy of success and determine a learner's readiness to meaningfully engage with content [46]. Research from expectancy-value perspectives highlight the subjective nature of value and distinguish between intrinsic (i.e., fun and enjoyable), attainment (i.e., important to who they are), utility (i.e., are useful and related to their goals), and cost values (i.e., the time and effort are worth it) [50]. Perceptions of value are related to higher enrollment in courses, out-of-school programs, and career choices and can trigger situational interest in an activity [52] and support learning and achievement [106].

The subjective nature of value means that what is important is not an objective or general value of the content, but rather the individual's perception of that value in relation to themselves or the people and community they care about [65]. These values are also mediated in part by the learner's perceptions of the values of society, at a large scale, and others in their learning environment, at a local scale, that also influences a learner's sense of belonging. In this way, the personal disposition of the learner interacts with the values and norms of the cultural context surrounding the learner's activity with and perceptions of the value of the content. The socio-cultural context also impacts the feedback the learner receives about their participation and how, where, and when learners are able to participate in activities of interest (e.g., computing) that all further impact their value for the content [7].

3.3 Belongingness

The third dimension of interest development that we incorporate into our framework is a learner's sense of belonging or connectedness with the content they are learning. This dimension is not typically included as a distinct dimension in prominent theories of interest development (e.g., the four-phase model of interest development [123]). However, more recent work in the field has highlighted the impact of belonging on interest and learning, as well as on developing knowledge and value [13]. Developing a sense of belonging, or not belonging, is thought to emerge as learners make sense and assign meaning to experiences that trigger their interest while learning [112]. Feeling a sense of belonging satisfies a basic human need for building relationships with others and the world around them, which motivates behavior [131]. This sense of belonging forms through building connections between a learner's existing experiences, background, and interests and new content being learned [5], by feeling connected with peers, teachers, and others in relation to the content [112], and through personal and social feedback about the learner's place amongst those who engage with and practice with the content [13, 93]. As with the reciprocal relationship between value and knowledge for interest development, a sense of belonging also builds a desire for knowledge and a perception of value that in turn support a sense of belonging. We demonstrate the bidirectional relationship between each of the three dimensions of interest development in our framework (see Figure 1), and throughout the article, we emphasize the importance of supporting multiple dimensions of interest to amplify the effects each dimension has on the others.

4 KEY FACTORS INFLUENCING INTEREST IN COMPUTING EDUCATION

In the previous section, we outlined the current state of interest development literature and presented the three major dimensions of interest. We now turn to computing education specifically and present key factors that link current interest development theory to the discipline. The goal in making these links is to help researchers design and align learning opportunities with interest theory and integrate multiple interest development dimensions across learning opportunities. For each key factor, we also discuss related pedagogical and design strategies that can be used to integrate the key factor into computing education learning experiences. While each list of key factors to support interest is not exhaustive, we believe they represent a strong foundation for designing learning environments in computing that promote interest. To illustrate each key factor and strategy, we conclude each section with examples from computing education research demonstrating what this key factor may look like in practice.

In presenting these key factors, it is important to recognize the need to both trigger (catch) and maintain (hold) a learner's interest, particularly in cases where existing interest is low. Triggering interest is often the focal point of many computing education interventions, with programs designed to catch a learner's interest by introducing novel and exciting technologies (e.g., e-textiles or robots [74, 78]) or by building around popular topics (e.g. video games or entertainment [95, 141]). However, to sustain and develop long-term individual interest, methods of *maintaining* interest, through relevant and meaningful activity, are crucial [125]. For example, DiSalvo and Bruckman

[36] found that forming a computing education intervention for young men around video game testing was effective in triggering interest and attracting their attention to the program, but that the lasting impact of the program was likely due to aligning with their values for identifying, connecting with, and feeling successful in a potential computing-related career that may have maintained that situational interest over time. Therefore, in our presentation of key factors of interest in computing education, we focus on means of maintaining situational interest towards developing long-term interest, organized around the three central dimensions presented above: building knowledge, finding value, and feeling belongingness (see Figure 1).

4.1 Building Knowledge for Interest

We begin by exploring how to foster interest development by implementing knowledge building or computational thinking supports in computing education. Both conceptual and skills-based approaches to learning in computing are common in computing education, as this is the primary focus of the discipline. It is rare that practitioners or researchers consider the implications of knowledge building on students' individual interest in computing, but building computational knowledge and competencies in ways that are appropriately challenging and that give learners a sense of what that knowledge is for can have a powerful impact on interest. Based on this connection, we examine the role of supporting knowledge in computing for interest in three ways: appropriately calibrated levels of *challenge*, *personally relevant* learning activities, and learning activities that represent *authentic practices* in computing.

4.1.1 Key Factor: Challenge. Providing learners with an appropriate level of challenge while learning in computing is a common approach in computing education. Learning environments and pedagogical approaches designed to find the right level of challenge for learners are linked to interest development research that suggests appropriate levels of challenge in a learner's work can also help trigger and sustain their interest [125]. Therefore, it is crucial that instructional designers use supports, or scaffolds, that are well-calibrated to match the challenge of the task to the individual learner's existing knowledge, skill, and interest in computing [114]. This means that supports cannot be applied universally, and computing education interventions should plan for the complexity of tasks and tools available in the learning activities to evolve over time to match the learner's ability. A low-interest and low-ability student may need to have scaffolds in place to demonstrate first steps in a computing task or how to think of the task in relation to bigger-picture problems. These learners may also benefit from a more heavily scaffolded programming environment, such as Scratch, to engage with tasks with a limited number of skills to manage, and would also benefit from a programming language designed to clarify and infer how to structure a program or how to implement a computational technique. As a learner's interest and ability progress, the challenge should increase, where this level of scaffolding is no longer needed and may inhibit both learning and interest development [120]. Learners with increasing knowledge and interest should be asked to work at a higher level of complexity and challenge where the tasks become more elaborate, such as nesting one computational problem within a larger challenge; and the tools they use become more sophisticated, such as using object-oriented programming language or developing their own subsystems or functions. Therefore, a deliberate plan to introduce and fade task and tool scaffolds should be included in computing education programs, including opportunities for learners to self-scaffold and choose when to add or remove scaffolds themselves to properly calibrate the challenge of learning activities. Knogler et al. [75] demonstrated the effect of scaffolded activities by increasing the complexity of a task that required learners to continually build their understanding of a problem that resulted in repeated triggering of interest across several activities. This type of complexity of the learner's environment may be quite effective in building interest

[49], but careful calibration of the difficulty of the learning task is necessary, as an activity that is too challenging or not challenging enough may spark frustration or boredom that will diminish situational interest [125].

Examples from Computing Education Research. A central design construct for the design of learning environments to ensure they are at an appropriate level of difficulty is scaffolding. The term scaffolding was coined as a means to describe interactions of a tutor supporting a student but has since been expanded to describe features of a learning environment designed to aid a learner with the intention of the support fading as the learner's knowledge grows [107, 118] that are commonly implemented as technology-mediated learning contexts [67, 115]. In the context of computer science, a variety of scaffolds have been proposed and studied, ranging from pedagogical approaches to specific features of programming tasks and environments. For example, the Use->Modify->Create instructional strategy serves as a means to introduce learners to a tool or concept by first having them use it, then asks them to modify an already working example using the tool or concept, and then finally, create their own program or project based on the idea. In this way, the instructional sequence serves as a scaffold to introduce the concept being learned [43, 84]. In particular, this scaffolding allows learners to grapple with the content at appropriate levels of challenge, where higher interest and ability learners can use, modify, and create tools and concepts at complex levels and lower interest and ability learners can work at levels of difficulty they are more comfortable with. Providing worked examples with subgoal labels is another example of a strategy to scale the level of challenge, within a single activity, which has been found to be effective at helping novices learn to program [88, 97]. Worked examples with subgoal labels present problem solutions to learners that show the steps an expert follows and add labels to each step that name the specific subgoals the expert is applying, thus providing additional structure on how to break down a problem at hand [24]. A third example of the use of scaffolds focused specifically on learning to program can be seen with the block-based programming approach, where the environment provides a suite of supports intended to help novices have early successes when learning to program [11, 146]. Both worked examples and block-based programming approaches can be implemented as scaffolds, where novice and low-interest learners benefit from the supports, and these supports can be faded to increase the challenge for more expert or interested learners. For example, high-interest learners may appreciate the challenge of creating their own subgoal labels for a worked example or benefit from translating a program written in a block-based language into a text-based language. Creating multiple adaptable layers of challenge increase the likelihood that situational interest is triggered for a variety of learners and can maintain interest over time as challenge increases.

4.1.2 Key Factor: Relevance. Providing learning contexts in computing that are personally relevant is another critical approach to supporting knowledge building in computing. Learners benefit from instruction and practice that is tailored to match their lived experiences and draw on their prior knowledge and cultural resources. There is strong evidence that a learner's experiences at home and around their community vastly impact how they learn in informal and formal educational spaces [21]. Intentionally designing for learning activities to be flexible enough to align with these experiences allows learners to personally relate and identify with the content that also supports developing interest [113]. A culturally relevant pedagogical approach is a powerful means of creating relevant learning environments, which empowers student voices and autonomy in what counts for learning and how it is assessed and draws connections between the learning environment, lived experiences, and community spaces, to cross-pollinate the beliefs, norms, and values of the community into learning [21, 79]. This culturally relevant pedagogical approach aids in learning, because learners better acclimate to the environment and find their perspectives and ways of knowing valued in the learning space. This approach also aligns with interest development theory in that it embraces the need to tailor learning experiences to integrate a learner's background, allow them to leverage their prior experiences and knowledge, and enables learners to feel empowered and capable in engaging with learning tasks [6]. Interventions in computing education can be designed to facilitate personally relevant learning experiences, and a culturally relevant approach engages the whole learner by allowing them to tailor the activities to match their own interests and background.

Examples from Computing Education Research. In an effort to make computing instruction relevant and in response to the growing recognition of the importance of creating learning experiences that draw from prior knowledge and cultural resources, a number of culturally responsive computer science curricula and tools have been designed and studied. Towards this end, researchers have created culturally sustaining design tools to teach computing that celebrate and incorporate cultural arts [40, 70, 110]. At the same time, entire computing curricula and outreach programs have been designed explicitly around the idea of culturally responsive computing, such as Scratch Encore, which situates computing concepts by presenting multiple pathways, or strands, through each learning module that were deliberately designed to celebrate multiple cultures and traditions that may resonate with youth from a variety of backgrounds [44]. COMPUGIRLS is another curriculum dedicated to culturally responsive teaching, which was a program designed to attract Latina and African American girls to computing by using digital media to support girls in developing computational thinking and technosocial skills while enacting a social justice agenda [137]. Another example of making computing relevant to learners by drawing on interest can be seen with the EarSketch project, where learners create music tracks by programmatically combining audio samples created by real music producers [85]. These approaches support knowledge and competency, allow the learner to feel the content is meaningful and relevant, and give teachers in computing opportunities and tools to build quality relationships with their students and between their students [4]. This feeling can have a dramatic impact on maintaining situational interest and is a complement to other interest supports for value and belongingness.

4.1.3 Key Factor: Authenticity. Finally, many computing programs have begun to embrace learning environments that reflect authentic computing practices by providing rich contextual scenarios and purpose for the knowledge and skill students are asked to develop while they are learning. Students can find what they learn to be more meaningful because they experience how computing is applied to real-world tasks rather than learning out of context. That is, a programming assignment done in a vacuum is inherently only about programming skills, but when done in the context of an authentic problem, say, computer vision for detecting pedestrians, learners leverage their real-world experiences and see the impact of their work [96]. The addition of authentic learning is in alignment with interest development research that suggests maintaining situational interest requires going beyond eye-catching or novel encounters with content, where meaning and value sustain engagement and build towards individual interest [49, 125]. Again, how the learning environment defines authenticity is important, and discourse and activities that support an expansive notion of what counts as computing is essential. For learners who have an emerging or well-developed interest in computing, authentic learning experiences, and feeling their work is authentic, can be crucial to connecting their own areas of curiosity and to better appreciate disciplinary knowledge as it applies to work with computing, particularly beneficial to those with emerging individual interest, and to connect to the wider world of computing as a discipline.

Examples from Computing Education Research. Two ways to incorporate authenticity into computing education contexts are through providing real problems for learners to work through and by presenting learners with authentic tools and resources to use. Problem-based learning is an instructional method that presents learners with complex problems drawn from the real world that do not have a single right answer and challenges students to identify a strategy to make progress on the problem and then engage in self-directed learning to try and solve it [59]. Research shows problem-based learning is an effective way to engage students in computing in both K–12 classrooms [138] and in higher education [71, 134]. One strategy for integrating authentic problem-based learning scenarios is to connect students with actual clients from outside the classroom, thus, turning course assignments into real projects, with the teachers serving both as instructor and as a consultant to aid the student teams [128]. Problem-based learning that has students use professional tools and materials can also bolster the authenticity of the work. For example, the CORGIS project presents learners with real-world datasets as a context to employ computational practices [9]. This approach of using tools and technologies aligned to professional practice is in contrast to using purely instructional tools, such as block-based programming, which has been critiqued by learners due to a perceived lack of authenticity [148]. Enhancing authenticity supports interest, as learners gain deeper knowledge within the context of real computing practices, build a sense of their own capacity for completing real computing work, and can see how computing fits into their world.

4.2 Valuing Computing for Interest

We now turn to the second major dimension for developing interest in computing: finding value in the content. Interest development and motivational researchers have demonstrated that finding value in what one learns is essential for sustaining long-term interest in academic content, such as computing, but the conceptualization of value in interest and motivation literatures takes many shapes, including personal value, utility value, and task value [50, 106]. For the purpose of this framework, we synthesize across these perspectives to identify two key factors in supporting computing interest through perceptions of value that are: (1) *personally meaningful*, when learners feel that what they are doing will have a positive impact on them or their community; or (2) *personally useful*, where learners feel what they are learning is valuable to other, related goals. For example, learning about environmental science might be personally meaningful if the learner sees how the discipline positively impacts quality of life for their friends and family or that societal impacts of global warming can be mitigated by knowledge about the environment. In contrast, personal usefulness is more about a means to an end, where, for example, success in a chemistry course is likely important for an aspiring medical student, so they value what they learn in that class, not necessarily for the chemistry, but what their knowledge of chemistry can do for their goals and aspirations. Clearly, values derived from personal meaning and usefulness are not necessarily mutually exclusive, but it is helpful to recognize the distinctions and attend to both when designing learning interventions in computing.

Currently, the most prominent approaches to supporting value in a content area are known as relevance or value interventions that apply either *direct communication* of the value of what is being learned or has students engage in activities where statements of the value are *self-generated* [50]. There is a rapidly growing body of literature around each approach, and researchers have explored many details and nuances about how and when to apply each. Both personal meaning and usefulness can be supported through direct communication or self-generation of value, which makes these versatile approaches that can be tailored to the needs and backgrounds of individual learners. In particular, there is evidence that direct communication may be better for learners with an already existing interest in the subject, and might be most useful when applied prior to the learning activities. Self-generated value statements may be better for students with lower interest and confidence in their abilities when they are directed to think of how what they are learning will have value in the near future [52]. In computing education contexts, supporting value through direct communication and self-generated statements is likely incorporated informally into programs, especially those that employ a mentored approach or incorporate messages about computing careers and the applicability of computing in their curriculum. Both direct communication and self-generated value can support the feelings of usefulness and meaningfulness, our key factors for the value dimension.

4.2.1 Key Factor: Useful. When learners believe that what they are learning is useful, the activity becomes more valuable and aids in triggering and maintaining interest and in developing long-term individual interest [49]. However, it can be difficult for learners with little experience, misconceptions about content, or who are learning content without real-world context to find the utility in activities. Usefulness or utility can take many shapes, including believing that what they are learning will directly contribute to personal goals, such as building technical skills for a career or gaining access to future learning, or indirectly, such as building communication skills for public presentations or math skills that might support other interests and careers. Given the number of ways that computing content can be useful, coupled with the potential difficulty in learners without existing interest to see that utility, it is important to help the learner draw clear connections between the content and their future goals. In practice, making this connection could occur through direct communication (e.g. with a reading or brochure [64]) of how learning computing can be useful for a variety of careers, for success in high school and college courses, or for other hobbies and activities. Learners could also be asked to self-generate these connections for what they are learning to relate to their career, educational, or hobby pursuits. Promoting a sense that what they are learning is personally useful is a key factor in building value for computing that requires alignment with existing perspectives, experiences, and goals. To aid in this alignment, computing education programs might benefit from incorporating this messaging into existing mentoring opportunities by training mentors to focus on the usefulness of computing in and out of traditional computing disciplines as they relate to each learner's background.

Examples from Computing Education Research. Given the growing role of technology and computing in the world, there are a number of computing education interventions that frame the subject as one that is useful to learn. For example, Clegg and colleagues have pursued a line of research seeking to help collegiate athletes better understand computing and data science by grounding instruction in the data collected about the athlete's own performance [29]. This work portrays the utility of the skills and concepts being taught as it relates to a central aspect of the athletes' lives—that of improving their athletic performance. For targeted groups, such as athletes, this type of value support may be most effective through direct communication, as it is likely connecting the value of computing to an existing interest, (e.g., athletic performance) that will resonate with the learners. A second example of computing intervention focused on building interest around utility can be seen in the work on Conversational Programming and efforts to create purpose-first programming [31]. The central insight with this work is that end-users care more about what a program does than how it does it, as such, instruction can foreground the abilities and utility of coding concepts and patterns to improve interest rather than focusing on technical details. In a pilot study of a purpose-first programming intervention, researchers found the approach motivating for learners, as it "engenders a feeling of success and aligns with these learners' goals" [32, p. 1]. This approach is similar to self-generated value interventions, in that the learner creates their own vision for the utility of the work, so the activities align with their goals. In both examples, researchers have leveraged the feeling that the activities are personally useful to promote value for learning computing that has positively influenced interest and motivation in computing.

4.2.2 Key Factor: Meaningful. Finding that activities and learning of content are personally meaningful also promotes value that enhances situational interest and builds individual interest in the content. Activities might be perceived as personally meaningful when they align with the learner's own values and beliefs or benefit the friends, family, and community that the learner cares about. Work on career choice has demonstrated this importance of alignment with personal values and beliefs in that these alignments bridge the gap between personal identities and motivated behavior, where participating in these activities is meaningful partly because they allow the learner to enact and validate their self-perceptions about their identity [39]. For example, learners might have a self-identity that incorporates a love of nature, helping others, or fashion, and will find activities that relate to these aspects of their identities to be personally meaningful. Activities can also be meaningful if they are perceived as beneficial to others that the learner cares about, such as family or their community, because supporting communal goals is related to personal roles and strengthening connections within these groups [113]. That is, when one has a social connection with others, contributing to their success or well-being is personally meaningful. Studies that have highlighted the communal benefit of STEM content, stereotypically seen as unrelated to communal benefits, while learning can enhance a sense of value for that content [20]. The importance of personally meaningful work in promoting value implies that computing education programs might adopt interventions that take a communal value approach or help build connections to personal values and identities to combat the stereotypes that might preclude learners from finding computing valuable. These interventions may be designed as self-generated value activities that ask learners to reflect on their own beliefs about how what they are learning can impact their community or align with their values and can even be effective by simply asking learners to reflect on their own values without making an explicit connection to the subject [50]. Combining self-generated values with other means of direct communication of how activities are meaningful can enhance the overall effect of the intervention approach [52, 65], where deliberately building in several opportunities to reflect on personal meaning throughout computing educational activities may continue to benefit the development of value and interest for computing. Highlighting personal meaning can be supported through written activity, but also through mentor and teacher conversations, activities designed to give students opportunities to work towards/on projects that are meaningful to them, or structured activities where peer reviews of computing projects include a section for learners to explain why they find the work important to them.

Examples from Computing Education Research. The idea of making learning experiences personally meaningful to the learner has a long history in computing education and is a foundational idea in Constructionist learning [105]. This principle can be seen enacted across a variety of computing education research projects where learners are given agency to shape the projects they pursue. For example, empowering kids to create computational artifacts about topics they are passionate about was a central design goal of the Scratch programming environment [126]. Here, learners apply computing to personally meaningful topics to provide an experience of computing that is consistent with their values and identity that might build value for computing. Other programming environments, such as Pencil Code, make it easy to embed images, animated gifs, audio, and video from the Internet into programming projects as a means to help learners personalize their programs and make them more personally meaningful [147]. This type of personalizing allows learners to bring their personalities and identities to bear in their work in computing that builds alignment between the work and their identity. Blikstein's work showed youths how technology and computing can serve as an emancipatory medium that impacts their communities, be it projects that blend music and religion or energy-saving devices that can help people in their neighborhoods [17], and Holbert's Bots for Tots project had youth build computationally enhanced "dream toys" for younger children, where learners felt building for others was meaningful [61]. In both of these examples, learners build value from feeling the work is personally meaningful through the support and impact it has on others that they care about. In sum, computing education has demonstrated a capacity for presenting computing as a personally meaningful activity to a broad range of learners by connecting computing to their existing values and identities, but in line with our review of supporting value, learners need opportunities and supports to make these connections. Supporting value through meaningful activities also provides a strong foundation for enhancing a sense of belonging in computing, as connecting learning to things the learner cares about and feels connected to strengthens their relationship with that activity.

4.3 Belongingness in Computing

Our third set of key factors for supporting the development of interest in computing is related to helping learners feel belonging and relatedness within computing and computer science as a subject and as a community. Considering belongingness introduces an inherent social factor to how interest is developed, where an individual's own perceptions of their identity and abilities, and their perceptions about how others see them, is considered in relation to their understanding of how one participates in an activity [13]. Importantly, this shifts the conversation from thinking about the subject as a set of skills, competencies, and activities, to also thinking about who it is that practices that subject and what it means to be a part of that community. Several factors affect a learner's sense of belongingness, including feeling that people similar to them participate in the discipline, that others recognize and affirm their belonging, that they are capable of engaging in tasks that are authentic and important to the community, and that they have a say in what counts as authentic work in that domain. In computing, persistent stereotypes about what computing and computer science are like and who practices them remain significant obstacles to feelings of belonging. To counter the issues with these computing stereotypes, we consider two main approaches to supporting belonging: expanding notions of what computing is and expanding notions about who can and should participate in computing.

4.3.1 Key Factor: What Computing Is. To expand notions of what computing is, researchers propose expanding what learners believe is the scope and purpose of computing and to what endpoint it may lead [143]. Learners can struggle to see computing and computer science beyond stereotypical notions of software engineering or programming, so presenting a broader vision of what CS is and how it can be used can help increase interest. By demonstrating and promoting computing as a broad discipline that encompasses games, arts, social interaction, and community engagement, we allow learners to feel that their personal interests can align with computing. Helping learners to connect their interests and identities to skills and practices in a discipline aligns with interest development literature on promoting belonging and relatedness in an academic discipline. When the learner can perceive a connection to the activities, particularly between their existing skills and interests and new activities, it can have a strong effect on triggering and maintaining interest that can lead to long-term individual interest [112]. Interest research suggests that learning environments can intentionally build pathways to connect a learner's background to the practices of a discipline [112] or can allow learners to tailor activities to connect to their interests and skills [6]. Learners who are given the power to shape the narrative about how and when to apply what they learn can make meaningful connections between content and themselves and their communities [16]. In computing, there are many opportunities to connect and tailor learning to meet learner needs that will help learners expand their notion of what computing is in ways that are congruent with their self-concept and identity. In computing education, learning environments can offer a multitude of activities, tasks, and ways of expressing competence in computing, provide opportunities to radically tailor activities to better match a learner's identity and existing competence, and create inclusive learning environments that limit the presence of stereotypical images and tools.

Examples from Computing Education Research. There are a growing number of curricula, tools, and learning experiences being introduced that present a vision of computer science beyond the programming-centric discipline it is often perceived as. One approach to broaden what learners believe computing is for is to focus on learner-driven exploration of computing. For example, the **Exploring Computer Science (ECS)** curriculum is designed around the notion of "computing with a purpose" and emphasizes creativity and opportunities for learner-driven exploration and problem-solving [109, 133]. Further, in constructing the curriculum, programming serves as only 1 of 6 modules, alongside topics such as problem-solving, robotics, human-computer interaction, and data analysis. In developing the pedagogy to accompany the ECS curriculum, the creators of the curriculum, with help from teachers, identify demystifying computing and addressing social impacts of computing as central practices [132]. Beyond formal curricula, the emergence of computing learning initiatives and environments focused around activities such as playing or designing video games [10, 152], making and digital fabrication [127], robotics [14, 30], arts and crafting [62, 70], storytelling [73], digital media [69, 108, 111], and social change [51, 142] all collectively serve in an effort to help learners understand the broader scope of what constitutes the field of computer science. In effect, broadening the perception of what computing is allows more learners to connect to computing and feel a sense of belonging in computing by acknowledging more forms of authentic participation in computing.

4.3.2 Key Factor: Who Does Computing. Expanding notions of who participates in computing, often by combating stereotypes, has long been a goal of computing education, particularly when focusing on broadening participation in the field. This is in response to the finding that many learners, especially racial minorities and women, do not feel they belong in computing [23, 81, 86, 87]. Learners intuitively assess their level of belonging by comparing themselves to others, including their perceptions of school culture and how they fit within that culture and their perceptions of what people who are good at an academic subject are like and how they fit that profile [60, 101]. The interest development literature recognizes the crucial role in feeling belonging or relatedness to develop interest in a subject area [60]. Motivational research has articulated how identifying as someone who can and does participate in an activity or community derives from a basic human need to relate to others we interact with, and is dependant on social and contextual influences and markers in an environment [34, 131]. Persistent stereotypes about computer scientists limit opportunities for learners to feel they belong in computing, including misperceptions in some regions that computing requires exceptional innate abilities or is a male-oriented field is socially limiting [26, 135]. The misperception that computing is for those with a special innate ability may even incidentally be perpetuated when role models are portrayed as *superstars* whose abilities may seem unobtainable [83]. Further, interactions with individuals or environments that reinforce stereotypes of computing, including that computer scientists are white, male, and interested in video games and programming, can negatively impact interest and a sense of belonging [25, 27]. Computing education environments need to intentionally demonstrate the wide breadth of people, cultures, skills, and backgrounds that represent computing, represent the contributions and participation of groups historically excluded from computing, and role models can provide feedback and meaningful interaction with learners that challenge traditional views and help learners to feel that they do in fact belong in computing as a practice [47]. This approach also connects deeply with building value for computing in that it helps learners feel that computing practices are meaningful to them and those they care about.

Examples from Computing Education Research. A central strategy for shifting perceptions of who does computing is the use of mentors [12, 116]. Research from outside of computing has shown mentorship to be valuable in both professional [66] and educational contexts [151]. In computing contexts, the use of mentors has been found to be important for shifting views of who does computing [19, 22, 38, 68, 111]. To reduce stereotypes and misperceptions about who belongs in computing, it is especially important to intentionally include mentors and facilitators from a diverse set of backgrounds [76], utilize exemplary work and sample applications that emphasize a range of different skills and attributes in computing [54], demonstrate how computing competence is built over time, and provide opportunities to form cohorts or groups that build a sense of community around computing [140]. Along with recruiting mentors from industry, research has also found that near-peer mentors, that is, mentors only a few years older, have been effective at helping shift learners' ideas about who belongs in computing [28]. Lee et al. [80] include a mentor and guest speaker component of their computing education program that can provide many opportunities for those speakers to provide testimonials about the value of the work, and its impact on their communities. Along with mentorships, efforts to directly confront and combat stereotypes about the field of computing, specifically strong gendered stereotypes held in some areas such as the United States, United Kingdom, and Sweden [3], help increase interest in students historically excluded from computing in those regions [90]. These examples highlight ways in which computing education can expand the notion of who does computing and what a computer scientist is like, and by recognizing many backgrounds and identities as legitimate participants in computing, we facilitate a sense of belonging for a greater number of learners.

5 MEASURING INTEREST AS AN OUTCOME

Research examining computing education programs and initiatives has built a theoretical and practical understanding of designing and implementing learning experiences in computing, and these programs often consider learner outcomes such as interest. However, when measuring interest, computing education research often fails to account for or draw on established theory in interest development or include sufficiently robust measures, which inhibits the ability to accurately interpret the true efficacy of interventions. For example, interest in computing is typically measured using a survey developed for individual studies, rather than a validated scale, often use a single survey item such as "I am interested in learning about programming," and rarely utilize multiple methods of estimating interest in computing (see for example References [35, 48, 100, 104]). These measurement approaches do not sufficiently capture the complexity of interest development and can be improved with better alignment with theory, development of standardized and validated instruments, and through triangulation with other measures including observational, behavioral, and interview techniques [89, 125].

5.1 Developing Self-report Measures of Interest

The most common method for measuring interest is the use of a self-report measure, using either a survey instrument or an interview. A valid and reliable self-report measure, whether as a survey or interview, asks individuals to respond to questions designed to reveal varying levels of interest and should be closely tied to a theoretical perspective on interest and utilize multiple items that capture the multiple facets of interest to improve reliability and validity. Surveys and interviews can be used in conjunction as multiple measures of interest to further increase the reliability and validity of estimating interest [93], but this approach appears to be rarely done in computing education. Here, we discuss the use and selection of self-report survey measures of interest and recommend interest scales developed for other content areas as a starting point for development of a reliable and valid computing interest survey. We then describe methods of utilizing semi-structured interviews as a self-report to capture a richer understanding of one's interest while maintaining close ties to interest theory.

In developing a self-report survey measure of interest in computing, it is important to distinguish between individual and situational interest as the intended construct. Typically, measures of interest are intended as measures of stable, long-term individual interest, but it is important to make this distinction both in practice, while creating or implementing the measure, and in reporting on the development and use of the measure. Measures of situational interest may also be of value in examining the development of interest in computing, but should be measured as a unique variable. It is also important to match the measures of interest used with the study design, where the length and depth of the computing experience, as well as the timing of the measure, will impact the utility of measuring individual or situational interest.

While individual interest is often what researchers would like to impact, and measure, as an outcome of a computing experience, it is a relatively stable variable that can be difficult to significantly influence, particularly with short or infrequent interventions. Therefore, in short-term studies, individual interest may be best limited to measuring it as a covariate that can be used to control for differences in individual interest when estimating the effects of the intervention on other outcome variables such as engagement or learning. It is more feasible to measure differences between pre-study and post-study individual interest in longer-term or high-frequency interventions such as camps, multi-week informal programs, or courses.

In contrast, situational interest can vary greatly, depending on environmental factors and personal dispositions [49]. As such, comparisons of situational interest should be used carefully, and influential factors such as differences in how learners engage with content, who is leading activities, or what other related topics are included in the activity should all be considered. As situational interest, particularly maintained situational interest, is considered to lead to individual interest, researchers in computing education may utilize measures of situational interest during short-term studies as indicators that the learning experience may be fruitful towards increasing individual interest over the long term, but caution should be used in how strongly this inference is made (see for example Reference [91]). Measuring changes and fluctuations of situational interest over time may also illustrate the process of interest development and how learners experience a computing education program. Here, multiple measures of situational interest at different time points, utilizing an experience sampling method [53], may be useful for examining these processes [82] and to examine how interest development relates to other features of the learning environment [15]. Making these clear distinctions between situational and individual interest in computing education research and matching the measures to the study design are critical components of moving the field forward in evaluating the impact of computing programs on interest. It is also important to improve the reliability and validity of the measures used and to design those measures to be operationalized from interest development theory.

To our knowledge, there is not yet an interest development scale developed and tested specifically for measuring computing or computer science interest. Some studies have included their own measures of interest in computing [48, 100, 104], but these measures can be improved with better alignment with interest development theory and through rigorous testing for reliability and validity. In particular, when using a measure of interest developed specifically for a study, we recommend that researchers include the theoretical background of interest development that was used to create their measures in written reports of research using those measures. This gives the reader proper background on how interest is conceptualized in the study and how the researchers operationalized the construct of interest to better interpret research findings. We also recommend that interest be measured with multiple items, ideally three or more, so internal reliability of the measurement can be assessed and that multiple facets of interest can be reflected in the items. For example, a researcher might include items that ask learners to report on their level of voluntary re-engagement with computing, their value for computing, and their feelings of belonging in computing. This multifaceted approach will allow researchers to capture a more robust conceptualization of interest.

While some researchers may prefer to develop their own interest measures tailored to the goals of their research, there are several interest development scales that have been developed for other STEM areas that can be consulted and modified for use in computing. The **Four-Phase Interest Development Scale (FIDS)** was originally developed to measure individual interest in a high-school engineering context and has demonstrated robustness to modification for other content areas such as reading and chemistry and educational levels including middle-school and undergraduate [92, 94]. This scale was developed through multiple rounds of testing and in close alignment with interest development literature. For individual interest, we also recommend the use and modification of the **Interest Development Survey (IDS)** [18]. The IDS scale includes 20 items that load onto five factors related to interest development and was created to be flexibly applied to a number of contexts and content areas. The multiple factors and wide range of items of the IDS make it a great candidate scale to examine how different facets of interest development manifest from a computing educational program. To measure situational interest, a scale developed by Knogler et al. [75] is able to capture catch (or trigger) and hold (or maintain) situational interest as two distinct factors and can be useful for computing education researchers who would like to examine situational interest at this grain size. Each of these scales represent useful tools for the computing education research community to implement and modify for their work, but the field would greatly benefit from robust evaluation of reliability and validity of a survey developed specifically for computing interest, and we would welcome the development of such a tool for the computing education community.

The same level of rigor in developing and utilizing a survey method of measuring interest should also be applied when designing interviews to estimate computing interest. Like a survey, interviews should operationalize interest theory in a clear and direct way, where researchers can tie each interview item back to interest theory and describe those connections in their written reports of the study. However, an interview method for examining interest will also require interviewers who are familiar enough with interest development theory to adequately craft follow-up and clarifying questions during interviews to effectively focus the narrative around interest, while creating a space for participants to provide rich descriptions of their perspectives and experiences. A semi-structured interview protocol can be quite conducive to creating this space and has been effectively used in prior work in other STEM disciplines. Used in conjunction with interest surveys, interviews provide a rich deep dive into participant experiences and help to triangulate evidence about interest (e.g., Reference [139]), but these measures remain limited in their self-reporting nature, where factors such as participants focusing on providing answers they believe the researchers want to hear or lapses in memory and judgment may bias each participant's responses. To further bolster the validity and reliability of interest measures, we also recommend utilizing behavioral measures of interest to present an additional lens on interest [2].

5.2 Incorporating Behavioral Measures

To utilize behavioral measures of interest, researchers can include observational and activity data to examine how learners engage and interact with content that can reveal information about their relationship to that content [121]. Common behavioral measures include voluntary re-engagement (i.e., how often learners voluntarily choose to participate with the content on their own) and examining the way they engage with content when they do participate. In a formal learning environment, observations of how frequently a learner engages in optional activities or continues an activity beyond required portions can also inform an understanding of their interest, but re-engagement measures can be especially beneficial in informal or out-of-school programs, where researchers can observe when participants participate, how long they are there each time, and what activities they spend their time doing. In particular, examining what activities learners participate in helps to establish specifics about topics or practices learners may have connected and can provide details about the process and specifics of their interest development [5]. These observations can also include time on-task measures [72] and discourse analysis to explore how what learners say shapes a perspective on their interest development [145]. Discourse analysis is especially useful in providing information about how and when situational interest is triggered, by both looking for occasions that learners vocalize when their interest is caught or in capturing conversations around parts of an activity designed to trigger interest [119]. In summary, research in computing education often includes qualitative and observational data collection to examine the process and experience that learners have in the learning environment, and designing research methods and conducting analyses to capture observable elements of interest development would make significant contributions to theory on interest in computing and in triangulating evidence about interest development and program effectiveness.

6 IMPLICATIONS

In creating the Integrated Interest Development for Computing Education, we set out to present the interconnected dimensions and key factors of interest development theory to inform the design of computational learning opportunities, particularly those focused on increasing and broadening participation in computing. Our hope is that by making interest a design priority in computing education, we support researchers in building more robust *theories* of participation and persistence in computing education and provide a framework for *design* in creating learning environments that foster interest. Advances in the conceptualization and measurement of interest will improve computing education researchers' ability to examine the process of interest development and the success of programs in developing interest. Those advances can inform increasing participation, as the field relies on and aligns with interest theory to meet the needs of learners, and broadening participation, as the field incorporates socio-cultural approaches to interest development that better account for and address the social and cultural structures and barriers surrounding the historical exclusion of women and learners who identify as Black, Indigenous, or people of color.

In light of these goals and the benefits of developing interest for learning and participation in computing, we encourage the computing education field to consider the following implications of this work to increase theoretical alignment with the interest development literature:

(1) To address issues in increasing participation in computing, interest should be considered a central design priority and outcome in developing and researching computing educational environments.
(2) To address issues in broadening participation in computing, knowledge, value, and belonging should be supported through expansive discourse and practices of what computing is, who participates in computing, and who has the power to shape that discourse.
(3) To improve efficacy and fidelity of interventions designed to foster interest, researchers and designers should better align their interventions with interest development theory as described in the framework.
(4) To address the multifaceted nature of interest, the curriculum, tools, and supports for interest development in computing should expand to address all three dimensions of interest in the framework.
(5) To build cohesive interest supports, curricular planning should design for each interest dimension to be complementary to also foster increases in other dimensions of interest.
(6) To improve understanding the process of developing interest in computing, measures of interest-related behaviors and evolving situational interest should be incorporated into longitudinal studies in computing education.

(7) To improve the validity and reliability of interest as an outcome, measures of interest should be multifaceted, based on validated measures, and developed in alignment with interest theory.

These implications point the field in a direction that utilizes and benefits from decades of work in interest development theory. The Integrated Interest Development for Computing Education framework provides a synthesis of that work and provides examples and a roadmap forward on implementing multifaceted and rigorous interest development supports in computing. However, much work remains to be done in computing education to better understand the complex nuances of interest development as it relates to computing, and in general, to build a larger corpus of domain-specific motivational theories and measures [99]. This work has drawn from research across informal and K–16 formal levels of education and is presented in a general format to be utilized across several age ranges. Future work that focuses on identifying interest development needs and processes for specific age ranges would improve the framework. We also encourage the computing education community to prioritize investigations that explore how to apply interest development theory to meet varying challenges and strengths of different cultures and regions across the globe. For example, women face exclusion and barriers to participation in some but not all regions and countries. As a field, we should examine and design instruction that builds on strengths while supporting other interest development needs. Furthermore, future work is needed to examine how knowledge, value, and belonging in computing interact and change over time to sustain or diminish interest in computing, as well as how to properly balance each dimension according to varying student development, interest, and background. A valid and reliable measure of interest in computing, specifically designed for computing, would improve the ability to accurately measure interest and can become a centralized measure to be compared across studies. Studies that examine other learning and motivational factors in computing that look at how these factors interact with and influence interest will further improve the field's understanding of computing education and afford a better learning experience for learners in these programs. Finally, studies that examine the role and impact of professional and workplace factors, outside of computing education environments, on the development of interest will better inform the ways we prepare learners to participate and continue their interest for computing in these spaces.

In summary, increasing the rigor of how we apply theory in computing education will vastly improve the field. The Integrated Interest Development for Computing Education framework is novel in unifying and synthesizing perspectives and dimensions of interest from across interest development research, highlighting the interconnectedness of these dimensions, and tying those perspectives and dimensions specific to the domain of computing education. We hope that our framework helps the field make strides towards better utilization of interest as a means for broadening participation and enhancing learning and that it informs the future work we look forward to.

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