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Undergraduate persistence in an open-access, online, scientific computing training is influenced by expectancy, value, and cost

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ABSTRACT

During 2020 a free, 3-month long, certificate-granting, online workshop was offered to increase undergraduates' knowledge, skills, self-efficacy, and interest in observational seismology and scientific computing. Course registrants were comprised of 760 upper-level undergraduates from across science and math majors, representing 60 countries. Performance data revealed 58% of registrants initiated the workshop by completing at least one assignment, and 30% successfully completed the full workshop. These rates were higher than most comparable large-scale, open-access courses. This study explores factors associated with persistence by examining registration, performance, and pre/post survey data through the lens of the expectancy-value theory (EVT). Results indicate that EVT constructs show moderate to weak associations with initiation, including intrinsic ($p<.001$), utility ($p<.001$), and attainment value ($p=.24$), and expectancy (e.g., completion intentions [$p<.001$], prior computing experience [$p<.001$], seismology research experience [$p=.01$], seismology self-efficacy [$p=.84$]). Two expectancy factors, academic major ($p=.050$) and prior geophysics coursework ($p<.001$), showed weak associations with completion. Demographic factors such as race, ethnicity, and gender were not associated with initiation or completion, but primary language showed an association with attainment and intrinsic values. Dissuading factors or costs were also captured through surveys. The few responses from non-completers limited the analysis. However, an examination of acute and accumulated costs suggests they may influence persistence, especially at completion. Based on these results, interventions are proposed to enhance persistence in future workshops. These include increasing motivational messaging, tailoring course structure to mitigate avoidable costs, and where possible, increasing communication to set time and effort expectations and showcase prior participants overcoming costs.

Introduction and motivation

The process of fulfilling undergraduate curricular requirements and transitioning to Science, Technology, Engineering, or Math (STEM) graduate programs to develop research skills and practices plays an essential role in positioning the United States as a leading force in the world's economy by solving challenges facing the nation (NASEM, 2018). The knowledge and skills of incoming graduate students can vary widely, especially quantitative (e.g., NASEM, 2020) and computational skills. As a result, there have been repeated calls for students to develop computational aptitudes across STEM disciplines to harness the data revolution (NSF, 2007, 2011, 2017). Within the geosciences specifically, the need for more computational skills, including data management and data analytics were identified as skills of critical importance to geoscience employers (Mosher & Keane, 2021). Although recent literature on computational thinking recognizes there is still no single definition for computational thinking (e.g., Lockwood & Mooney,

2018; Tang et al., 2020), we find merit in Weintrop et al.'s computing-based conception (2016) which emphasizes the combination of data practices, modeling and simulation practices, computational problem-solving practices, and systems thinking practices. However, the most effective way to develop these skills within a discipline is not well understood, especially at the undergraduate level. Within the geosciences, there is no clear roadmap for all undergraduates to develop this expertise, nor is there a generally accepted threshold for what is adequate skill development (Mosher & Keane, 2021).

Some undergraduates gain such skills through participation in research opportunities, such as the National Science Foundation (NSF) funded Research Experiences for Undergraduates (REU) in the US, which have been shown to develop a range of research skills including data analysis, interpretation, and other technical skills (e.g., Bauer & Bennett, 2003; Junge et al., 2010; Thiry et al., 2012). Such opportunities are limited in number and highly competi-

tive with selectivity rates for the geosciences around 10% (Walters et al., 2016). Others may develop scientific computing skills within coursework. However, this can be challenging for students as science courses may prioritize the learning of disciplinary content over than the development of scientific computing and data analysis skills within a discipline (Weintrop et al., 2016). Even when these skills are included, the vertical alignment and scaffolding of skills across an entire undergraduate program, in courses taught by multiple faculty, seems unlikely. Alternatively, some undergraduates pursue these skills through a computer science course. While these teach the basics of programming, this is rarely within the framework of geoscience data analysis. The combination of a lack of intention and structured access may contribute to Mosher and Keane's conclusion that computer programming and data analytics skills may be difficult to get in the regular course of study (2021). Thus, many students currently in the geoscience pipeline could benefit from supplemental, discipline-based training opportunities in scientific computing, offered outside of the academy.

The role of the SAGE facility in the seismology learning ecosystem

Like most STEM fields, institutions of higher learning are the primary pillars of the seismology learning ecosystem. However, research facilities such as the NSF's Seismological Facility for the Advancement of Geoscience (SAGE) facility, operated by the Incorporated Research Institutions for Seismology (IRIS), have taken on an increasing role through their Education and Outreach Programs. As directed by the seismology community, the SAGE facility has provided instruction directly to students where appropriate for the advancement of the field. For example, IRIS facilitated summer research internships for more than 250 undergraduates since 1998 (Hubenthal, 2019), hosted a technical webinar series for advanced students and faculty reaching nearly 7000 viewers annually, and has run numerous workshops and trainings for undergraduate and graduate students (Taber et al., 2015). Such direct-to-student instruction empowers students to become the next generation of facility users and extends the impact of the NSF-funded facility by enhancing understanding of the facility and the facilitation of the latest tools and approaches to search for, request, and use seismic data.

A key example of this external, direct-to-student instruction has been a series of 3- to 5-day short courses from 2009 - 2017 (IRIS, 2021). Alternating annually between introductory and advanced graduate student audiences, the short courses pushed the community to explore new ways to use very large datasets effectively and embrace the quantity and complexity of the data resulting from an unprecedented, continental scale experiment (Aderhold et al., 2021). Most short courses employed "traditional instruction" consisting of lectures to introduce the seismic computing topic and key operations followed by a series of step-by-step instructions to code. However, prompted by a desire to offer something informed by recent educational research, coauthor Brudzinski developed an initial set of tutorial-based, active e-learning modules (Sit & Brudzinski, 2017) to deliver basic scientific computing training. The interactive assignments used a learning management system (LMS) to provide instructions for performing scientific computing tasks that were regularly evaluated using embedded questions that also delivered real-time feedback and guidance for incorrect responses. Simultaneously, these modules were also piloted and then integrated as a staple of the IRIS summer research internship program.

In 2020, the COVID-19 pandemic created large disruptions to most educational systems. This disruption extended to REU programs (Sloan et al., 2020), including IRIS's that uses virtual tools to collaborate and build cohorts at multiple sites across the country (Hubenthal & Judge, 2013). This left a tremendous gap in the seismology educational ecosystem impacting both graduate and undergraduate learners and was identified as a critical need during IRIS's (Hubenthal et al., 2020) and the American Geophysical Union seismology sections' (Dugick et al., 2021) pandemic response.

To address this need, IRIS staff time and financial resources were reallocated to quickly ramp-up the development and delivery of a free Seismology Skill Building Workshop (SSBW). The goals of the SSBW were to increase undergraduates' knowledge, skills, and interest in observational seismology and scientific computing, self-efficacy in using seismic data, and competitiveness in the application process for graduate school, summer internships, or professional jobs (for a full workshop overview see Brudzinski et al., 2021). Despite their infrequent use in the geosciences (Mosher & Keane, 2021), the authors employed a Massive Open Online Course (MOOC) design.

A MOOC is course made available over the Internet without charge to a very large number of people. Since anyone who decides to take a MOOC simply registers, MOOCs have a tremendous potential for impact and global reach. For example, the World Economic Forum reports that a global audience of 92 million users registered for Coursera, one of the most popular MOOC providers, though now offered as a low cost rather than free option (Wood, 2022). Although the SSBW is smaller in scale, 760 registrants from 60 countries were empowered in 2020 to learn scientific computing within a seismology context at a flexible pace, and without financial restrictions associated with participation in a traditional course (Brudzinski et al., 2021).

MOOCs have tremendous potential, but they are also notorious for having low completion rates (e.g., Cagiltay et al., 2020, Jordan, 2015, Ho et al., 2014, Khalil & Ebner, 2014). For example, in a study of the MITx MOOCs, Cagiltay et al. (2020) found completion rates between 2% and 4% depending on the course subject matter. Therefore, understanding student motivation and how they may evolve from registration to initiation to completion is important. Student motivation may have been particularly important in the case of the 2020 SSBW as 25% of registrants completed all assignments and 29% completed 80% of the assignments (Brudzinski et al., 2021); rates well above typical MOOCs.

Theoretical framework

Previous studies have identified student motivation as one of the main factors that can impact MOOC completion rates (e.g., Abdullatif & Velázquez-Iturbide, 2020; Badali et al., 2022; Chaw & Tang, 2019; Maya-Jariego et al., 2020). However, it is still unclear exactly which types of motivational factors influence learners' academic choices to persist in MOOCs (Badali et al., 2022). For example, Badali et al. (2022) found that academic motives play an important role in MOOCs retention. Maya-Jariego et al. (2020) reported the intensity of initial motivation was positively related to the satisfaction and perceived quality of MOOC experience. Luik and Lepp (2021) found a statistically significant higher ratio of completers to non-completers in the opportunity motivated (e.g., those who felt the course was the only possibility or suitable opportunity to study an interesting topic), success motivated (e.g., those who felt the course provided knowledged they needed to be successful), and interest motivated (e.g., those who were just generally interested in the topic of the course) groups of learners. Abdullatif and Velázquez-Iturbide (2020) found that internal motivation strongly affects intention to continue with MOOCs. Chaw and Tang (2019) showed that believing and having confidence in one's ability to perform well, valuing learning for its usefulness, importance, and relevance, and learning to solve problems and develop skills were positive motivations which promotes an increased tendency to complete MOOCs.

As illustrated above, much of this research has focused solely on students' positive motivational values. The expectancy value theory (EVT) provides a useful lens for examining such achievement choices (e.g., persisting in a course that is free and not offered for credit after registering) because it allows for negative motivational values, such as perceived cost, which has been less well studied in MOOCs (Wei et al., 2024). However, very few studies have applied this approach to MOOCs previously.

EVT is a multidimensional approach to examining students' motivations, which the theory suggests are determined primarily by students' expectancies for success on the task and the extent to which they value the task (e.g., Eccles et al., 1983; Wigfield et al., 2016; Wigfield & Eccles, 2000, Eccles & Wigfield, 2002) (Figure 1). In turn, many researchers have shown that students' expectancy-related beliefs and task values predict their performance and course-taking in STEM fields (e.g., Meece et al., 1990; Musu-Gillette et al., 2015; Simpkins et al., 2006).

Expectancy refers to students' current beliefs in their ability to be successful at a task and students' beliefs about their abilities to continue to be successful in the future (Eccles & Wigfield, 2002). Expectancy is like the concept of self-efficacy (e.g., Bandura, 1997; Pajares, 1996). However, expectancies generally refer to broad abilities or domains (e.g., Math), while self-efficacy can generally be thought of as referring to a specific task or skill within a domain (Hulleman et al., 2016). Expectancy is often considered together with students'
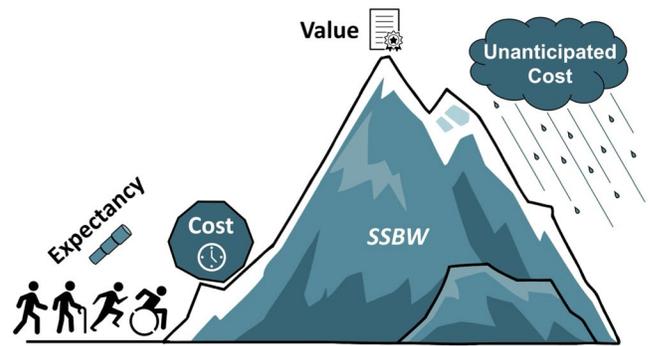
Figure 1. Diagram illustrating concepts of expectancy value theory in a generalized association to the SSBW, where expectancy is a student's perception of ability to complete tasks, value is perception of task merit, and cost is perception of consequences for participating, some of which may be unanticipated.

current ability to complete a task to create a broader construct of competence-related beliefs (e.g., Simpkins et al., 2006; Wigfield et al., 1997).

Values, on the other hand, describe a student's perception of the task's merit that might motivate learners to engage with the tasks (Eccles & Wigfield, 2002). These values can be described across three major categories; 1) the intrinsic value or the enjoyment or satisfaction a learner anticipates that they will experience from engaging with a task (Wigfield & Eccles, 2000), 2) the utility value or the perceived usefulness or importance of a task on a learner's current or future goals (Wigfield & Eccles, 2000), and 3) the attainment value or the perceived importance of the task to the learners self-concept or identity (Eccles & Wigfield, 2002).

In addition to these values, Wigfield and Eccles (2000) also describe a collection of factors that might dissuade a learner from engaging in tasks. These dissuading factors, referred to as "costs", include perceived emotional or psychological consequences, such as the possibility of failure at the activity, the effort of doing a task, and the consideration of what students are not able to do because of their participation in the activity (Wigfield et al., 2017). In some cases, such as the consideration of what students are not able to do because of their participation, these costs may be anticipated by students. However, in other cases, such as perceived emotional or psychological consequences, or unexpected life events occurring (e.g., personal or family illness), they may also be unanticipated.

Research questions

This study seeks to understand the following context related questions with the goal of using the results to redesign or develop new interventions to improve future outcomes.

- What motivational factors are associated with students' decisions to continue past registration and initiate the 2020 workshop?
- What motivational factors are associated with students' completion of the 2020 workshop?

Study population and setting

The SSBW did not seek to recruit participants from a geographic region, so this free workshop opportunity was advertised to students and faculty through a mix of electronic mailing lists that reach both US-based and international audiences. Examples of such lists include those offered by IRIS, American Geophysical Union, National Association of Geoscience Teachers, and the IRIS social media channels. Announcements were re-shared and forwarded, but the extent to which this happened is not fully known.

The workshop was not offered by an academic institution, so no academic credit was offered to students for completion of the workshop. Instead, a detailed, module-by-module performance report was offered at the conclusion of the workshop (Brudzinski et al., 2021). Such completion reports or certificates are common in noncredit education as they provide information required for seeking credit at their own institutions (Clark, 2005; D'Amico et al., 2020) or recognition on a resume or professional portfolio.

The 2020 SSBW ran from June 1 to August 31 with an expected student time investment of 5-6 h/week. The workshop was divided into seven 2-week-long modules, each with two synchronous hour-long webinars recorded for asynchronous viewing. Webinars introduced seismological and computational concepts while also emphasizing how a seismologist might think about and approach the dataset or methodology. Additional participant-instructor and participant-participant interaction occurred through a regularly used Slack workspace.

Each module consisted of 5-7 interactive assignments constructed using a tutorial-based, active e-learning approach (Sit & Brudzinski, 2017) (Figure 2) that introduced a spectrum of observational seismology concepts likely to be encountered in graduate school, integrated with computational skills. Assignments provided participants with step-by-step instructions and justifications for performing real-world scientific computing tasks on a Linux virtual machine (VM). Participants' understanding of these tasks, their applications to seismological concepts, and their numeracy and spatial reasoning skills when interpreting code output were assessed using questions embedded regularly throughout each assignment. Feedback for incorrect responses encouraged reflective thinking and reinforced learning. These assignments were delivered through the Moodle LMS, while scientific computing occurred locally *via* a VM with pre-installed software that participants downloaded and installed on their computers. The VM was a critical element that ensured a common operating environment necessary for instructors to anticipate the exact products and errors that might be produced by students as they worked.

As reported by Brudzinski et al. (2021) the workshop received 760 undergraduate (including recent graduates ~1 year out from graduation) STEM majors residing in 60 countries. Registrants were primarily Geology ($n = 246$), Geophysics ($n = 161$), and Earth Science ($n = 137$) majors. However, 30% came from other STEM fields such as Engineering, Physics, and Computer Science. Just under half of the pre-survey respondents (47%) described their gender as female and 2% described their gender as nonbinary. Ages ranged from 19 to 66 years old with 66% falling within the "traditional student" range of 19 and 23 years of age. Further, 41% of respondents identified as a race or ethnicity that has been traditionally underrepresented in the geosciences within the United States. A majority (69%) were graduating within a year of the workshop or had recently graduated. Few had previously conducted research in seismology or geophysics (15%). Participants' experience with the workshop software was generally limited (e.g., Linux/Unix (14%), Python (28%), SAC (5%)). Over 62% of pre-survey respondents had previously taken at least one online course, and 66% of those indicated that they would recommend an online course to other students.

In the evaluation of the workshop, Brudzinski et al. (2021) concluded that of the 760 registrants, 440 completed at least one assignment, 224 completed at least 80% of the assignments, and 191 completed all 35 assignments. They also found that participants who completed all assignments
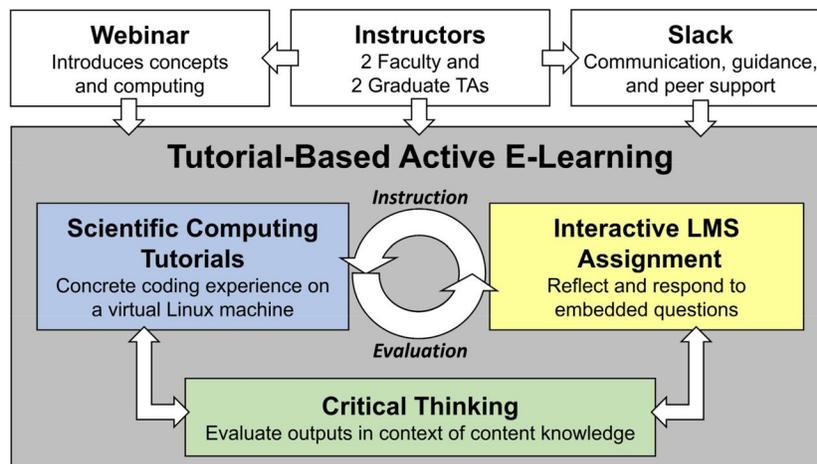
Figure 2. The SSBW employed a tutorial-based, active e-learning approach where interactive assignments within the LMS provided instructions for performing scientific computing tasks that were regularly evaluated using embedded questions. The design sought to inspire critical thinking when evaluating coding outputs and when responding to seismological questions. Participants were prepped for the active e-learning with webinars and introductory reading. Modified from Brudzinski et al. (2021).

showed normalized gains in scientific computing skills at >60%, interest in seismology, scientific computing, and graduate school at 47%, and perceived preparedness to apply to graduate school in seismology and to seek employment at 37%. Importantly, they noted that the workshop may have provided more equitable access to the field of seismology. The percentages of females (61%) and underrepresented minorities (20%) completing the workshop were greater than those receiving geoscience undergraduate degrees annually in the United States (Gonzales & Keane, 2020).

Research design

The development of this project did not originally center around EVT due to its development in response to the urgent demands of the COVID-19 pandemic. Instead, the data was collected by conducting a contextual evaluation *via* participant survey to identify and diagnose problems or barriers which might inhibit attainment of course goals and objectives (Stufflebeam & Shinkfield, 2007). This evaluative process was intended to facilitate continuous enhancements to the course structure in future years.

However, upon obtaining the survey data, the project naturally evolved toward investigating the factors influencing student behavior within a MOOC environment, with a focus on attrition and retention. This shift in focus prompted the formulation of research questions aimed at unraveling the determinants of participant engagement. Consequently, a correlational research design was employed to use a subset of the data collected during the contextual evaluation to assess participant motivation. This methodological choice was necessitated by the challenges associated with identifying and controlling influencing variables in a non-experimental setting (Privitera, 2014). Through the implementation of the correlational research design, this study explores potential associations between demographic characteristics and motivational factors, as interpreted through the framework of the EVT, and the persistence of registrants within the course.

The authors of this study served as the instructors for the SSBW in addition to researchers on this project. The lead author also identifies as a science teacher educator with functional coding skills and very limited seismic data analysis experience, while the second author identifies as a geoscience educator and seismologist with expert coding and seismic data analysis skill. These backgrounds lead the authors to approach this research with a keen desire to enable student success to the greatest extent possible. Participation in the research was optional for students, and the solicitation to participate was separated from the instructors. Once collected, the data was also anonymized prior to analysis. To enhance the trustworthiness of the interpretation of data collected the authors employed three strategies. First, they engaged in ongoing reflection and critical self-awareness regarding their own positionality. Next, they sought out peer debriefing by presenting preliminary results and interpretations to colleagues at informal meetings and conferences. To respond to this project's research questions regarding students' motivations, a subset of the 2020 SSBW evaluation data sources were used (Brudzinski et al., 2021). These included registration form data, pre- and post-survey data, as well as performance data captured by the LMS. All students completed the registration form. The pre-survey was administered to all workshop registrants and included an item measuring participants' "Completion Plans", which have been shown to serve as a benchmark for completion of other MOOC-style courses (Reich, 2014). The workshop post-survey provided information about students' perceptions of and satisfaction with the workshop, challenges they faced in completing the workshop, perceptions of changes in skills and interest in scientific computing in seismology, as well as future intentions related to scientific computing in seismology. Three different versions of a post-survey were administered to participants depending on the degree to which the participant completed the workshop. Response rates for each of these data sources are described in Table 1. Items constructed to evaluate the SSBW were assessed for face validity by sharing them with other education professionals' familiar with seismology and scientific computing. Items were also piloted with potential users. Pilots were only completed with US-based users as the large international participation in the course was not anticipated. All surveys were English language, matching the course materials, and averaged a Flesch Reading Ease score of 51, which falls within the "Fairly Hard to Read " category and correlates to a tenth to twelfth grade reading level (Flesch, 1981).

Due to the rapid development and rollout of the workshop in response to the pandemic, items on the survey were not intentionally developed with the EVT theory in mind. Rather, the evaluation items were developed based on the authors' experience working with students in similar settings

Table 1. Data sources used in the evaluation and the response rate to each. Additional details in supplemental materials.

Data Sources	Description	(n)	Response Rate
Registration Data	Basic information (e.g., academic institution, major, perceived incoming skills, etc.)	760	100%
Pre-Survey	Demographic and background information (e.g., gender, race, ethnicity, parental education, previous online course experience, English proficiency, enrollment reasons, etc.)	336	44.2%
Post-Survey (Completers)	Perceptions of the SSBW and the impact of the workshop on students	84	77.1%
Post-Survey (Partial)	Perceptions of the SSBW and reasons they did not complete the workshop	84	46.7%
Post-Survey (Non-starters)	Reasons they did not start the workshop	26	8.0%
Learning Management System	Performance data including time on assignments, number of attempts used, accuracy, completion, etc.	All	NA

and academic programs, and a desire to provide useful information to support continuous improvement of the workshop in future years. For example, participant registration forms provided information about academic majors, anticipated graduation dates, students' prior experience with geophysics and seismology including coursework, prior research experiences, and self-reported experience with scientific computing. Demographic information, students' reasons for registering for the workshop, prior experience with online learning, parents' highest degree, citizenship status, self-reported English proficiency, and students' self-efficacy related to scientific computing in seismology were collected from items on the workshop's pre-survey. However, during the data analysis phase after the 2020 SSBW, these data were organized using EVT as a lens for understanding student motivation. The following broad constructs that describe registrants were ultimately created: demographics, expectancy, and value (Table 2).

Where applicable, multiple survey items measuring concepts that are conceptually connected were summed to create a single sum score for each factor. This approach was employed as the use of multiple items helps to average out errors and specificities that are inherent in single items, thus leading to increased reliability and construct validity (DeVellis, 2003). While statistical tests for internal consistency might be expected, the repurposing of an evaluation survey resulted in only a small number of items per multi-dimensional construct with each measuring a related but distinct aspect. For example, participants' self-reported abilities to use each of the five scientific computing tools (e.g., Linux, GMT, Python, Jupyter Notebooks, and Matlab) were summed to create a holistic scientific computing experience score. Similarly, scores were calculated for Utility, Attainment, and Intrinsic value factors by assigning $a+1$ for each reason that registrants selected from a list for participating in the workshop (see supplemental materials for full description).

Considering the similarities of the SSBW to a MOOC, this study was designed to identify factors that may have motivated registrants at two key points in the workshop

Table 2. Organization of evaluation data based on the Expectancy Value Theory (EVT).

Construct	Factors
Demographics	US Citizenship
	Primary Language
	Familiarity w/ English
	Age
	Gender
	URM Status
	Parent's Degree
	Anticipated Graduation Year
Expectancy	Intention to Complete
	Academic Major
	GPA
	Perceived Computing Ability
	Would Recommend Online Course (If taken)
	Prior Seismology/Geophysics Research Experience
	Prior Research Experience (Other)
	Seismology Self-Efficacy
	Prior Seismology/ Geophysics Course
Value	Utility
	Intrinsic
	Attainment

completion process. The first was whether a student converted from registering for the workshop, a relatively low effort task, to initiating work on the workshop materials. Initiation was determined by examining data from the LMS. Registrants who logged into the LMS and completed at least one question in an assignment were considered to have initiated the workshop. Those who either never logged in or logged in but did not attempt any questions were considered non-initiators.

The second was whether those that initiated the workshop persisted to successfully complete it. Completion was measured for all participants who initiated the course. Completers were defined as those who initiated the course and successfully completed 100% of the workshop assignments. Those who initiated the workshop but did not reach this completion threshold were categorized as non-completers.

A range of factors collected were compared to these two binary outcomes (e.g., "Did not Initiate/Initiated" and "Did not complete/Completed"). Each factor and its levels were then tested for possible association with each of the outcomes using Chi-squared test of independence or Fisher's exact test, both in R, as appropriate for the data. Factors with a significance at, at least, the .05 level were identified and their effect size was determined using Cramér's V (Cramér, 1946). Effect sizes were then interpreted depending on the degrees of freedom as either weak, moderate, or strong (Cohen, 1988) and reported. While this single variate analysis is simplistic, it was deemed a reasonable starting point since the data collection tools were not designed with EVT in mind.

To estimate costs in the context of EVT, we used a question asking for reasons students did not initiate or complete the workshop. This offered *a priori* choices based on the authors interactions with students who dropped out along with an open-response option "Other, please describe". This pairing allowed unanticipated themes, not present in close-ended choices, to be identified. Data from the open-response option was analyzed by both authors using a thematic analysis approach (Braun & Clarke, 2006). The lead author used a recursive process where responses were read and organized around major themes that emerged from the data and represented participants' experiences without losing the detailed nuance of the individual responses. To enhance dependability, themes and responses were iteratively reviewed with the second author throughout the coding process. When disagreement occurred, the authors worked to refine and revise the constructs that underpinned each code and tested the efficacy of revisions by exploring the inclusion and exclusion criteria across multiple text samples. Any responses that were deemed ambiguous or nonsensical were placed in a miscellaneous category.
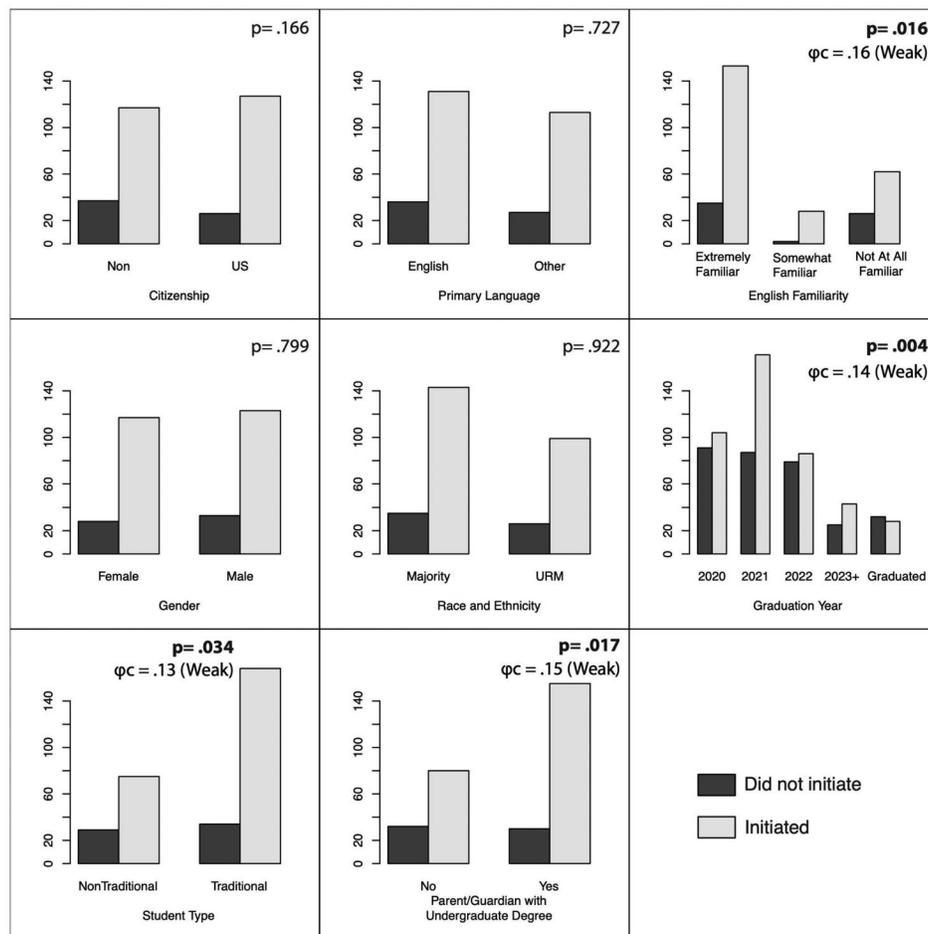
Results

Converting from registration to initiation

Testing the demographic factors found that registrants' underrepresented minority status, gender, and US citizenship did not associate with starting the workshop (Figure 3).
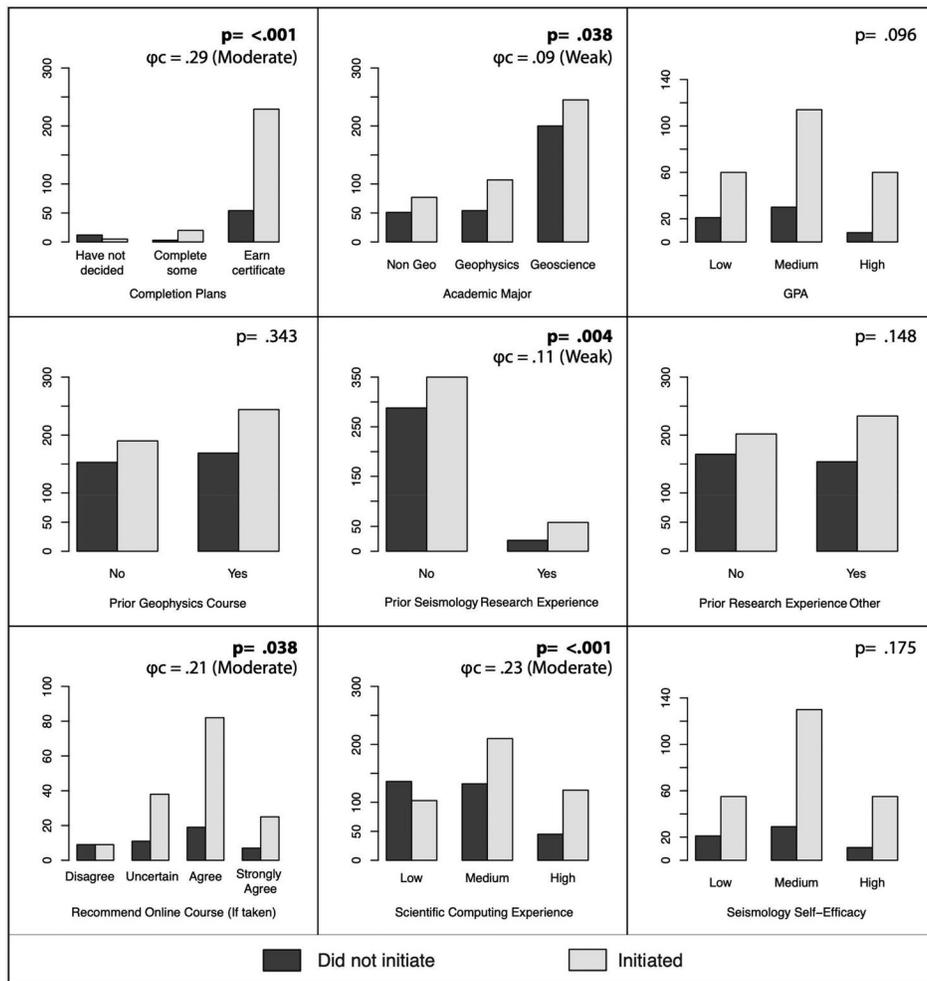
Figure 3. Associations between workshop registrants' demographic factors and their initiation (light shading) or not (dark shading) in the workshop as measured by first assignment completion. The number of participants for each factor is illustrated on the y-axis. Factors with a statistically significant association to registrants' initiation at ≤.05 level are highlighted in bold with the strength of association φ_c shown.

This was a particularly important finding given that the SSBW was designed in part to increase access to seismology and scientific computing training. English as one's primary language also did not associate with starting the workshop. However, one's familiarity with the English language did have a statistically significant, weak association. Registrants who reported being 'Not at All Familiar' with the English language initiated less frequently than those who were 'Somewhat Familiar' or 'Extremely Familiar' with the English language. Three other demographic factors also showed a statistically significant weak association with starting the workshop (Figure 3). Students who were one year or three years from graduation started the workshop at a greater rate than those who were graduating, two years from graduation, or had already graduated. Traditional students and those students whose parents or guardians had earned an undergraduate degree were also more likely to begin than nontraditional students or those whose parents did not earn an undergraduate degree.

Results from the expectancy factors revealed a statistically significant association with initiation for five of the nine factors we identified (Figure 4). Prior experience conducting seismology research did show a statistically significant weak association with starting the workshop. Registrants' academic majors showed a similar pattern of association with geophysics and geoscience majors being slightly more likely to not start the workshop than non-geoscience majors. Three expectancy factors showed a statistically significant moderate association with initiation: completion plans, scientific computing experience, and whether they would recommend an online course (for those who had taken an online course previously). Specifically, students who planned to complete some or all of the workshop were more likely to start the workshop than those who were undecided at the time of registration. Similarly, registrants reporting medium or high scientific computing skills at the outset were also more likely to start the workshop than those with low scientific computing skills. The remaining factors (grade point average (GPA), prior geophysics course work, prior research experience in fields other than seismology and geophysics, and a seismology self-efficacy score) did not show any statistically significant association between starting and not starting the workshop (Figure 4).

Value was estimated based on students being asked to select the reasons why they registered for the workshop from a list of nine items. Reasons were sorted as utility value, intrinsic value, and attainment value (see supplemental materials for full description). The number of items selected within each type were tabulated for each student and then analyzed for association with whether
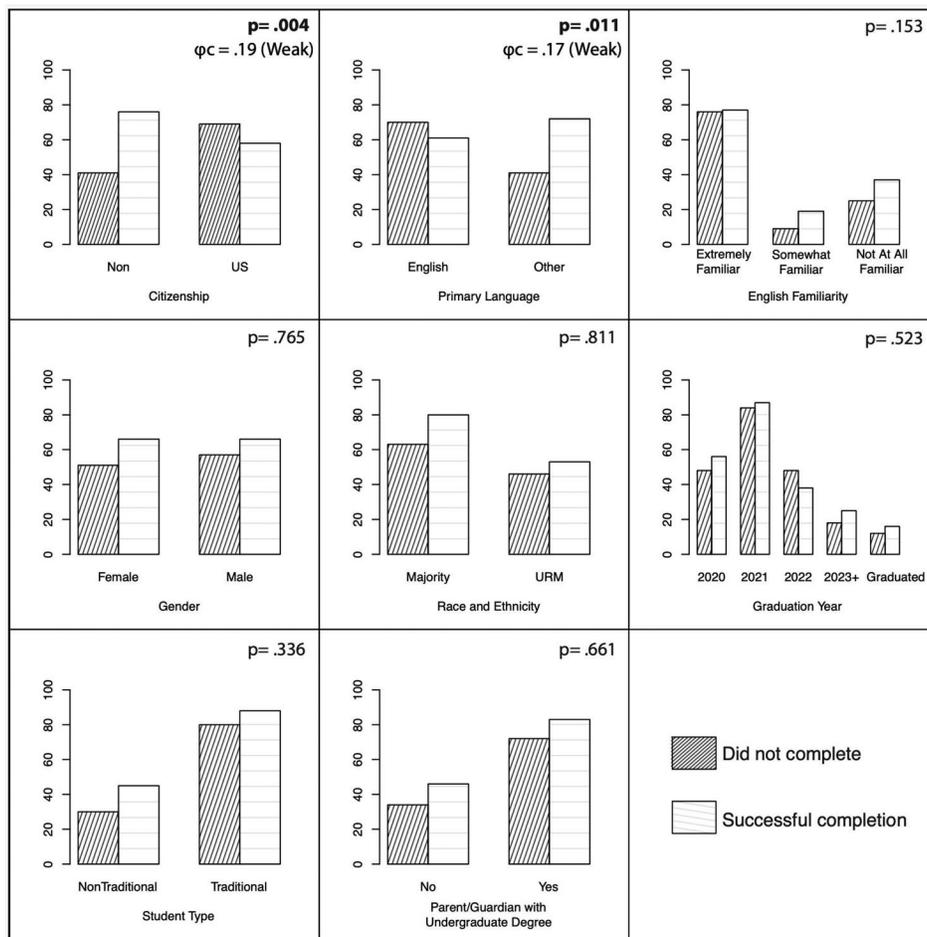
Figure 4. Associations between factors that align with expectancy, or students' current and future beliefs in their ability to be successful at a task. and whether registrants initiated the workshop (light shading) or not (dark shading) as measured by first assignment completion. The number of participants for each factor is illustrated on the y-axis. Factors with a statistically significant association to registrants' initiation at ≤.05 level are highlighted in bold, with the strength of association φ_c shown.
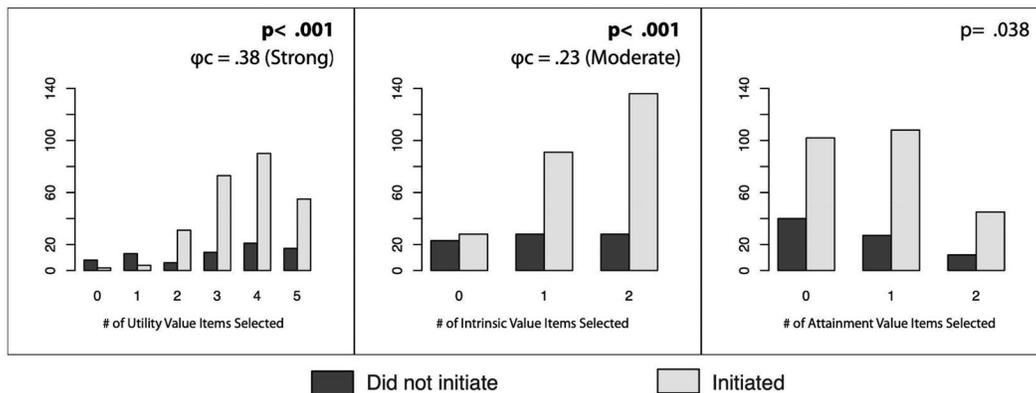
Figure 5. Students were asked to select reasons they registered for the workshop from a list. These reasons were grouped by value type: utility value (max = 5), intrinsic value (max = 2), and attainment value (max = 2). The association between value types and whether registrants initiated the workshop (light shading) or not (dark shading) as measured by first assignment completion are shown. The number of participants for each factor is illustrated on the y-axis. Value types with a statistically significant association to registrants' initiation at the ≤.05 level, are highlighted in bold with the strength of association φ_c shown.

registrants initiated or did not initiate the workshop (Figure 5). Results indicate that for all value types, the number of items selected were associated with a greater percentage of registrants that initiated the workshop. However, these findings were only statistically significant for utility value and intrinsic value, not for attainment value. The effect size was strong for utility value and moderate for the intrinsic value.

Figure 6. Associations between demographic factors of students who initiated the workshop and their successful completion of the workshop (light shading) or not (dark shading). The number of participants for each factor is illustrated on the y-axis. Factors with a statistically significant association to registrants' initiation at ≤.05 level are highlighted in bold with the strength of association φ_c shown.

Table 3. Comparison of conversion rates from initiation to completion based on participants' citizenship and primary language.

	English			Other		
	Completer	Initiator	Conversion %	Completer	Initiator	Conversion %
Non-US	12	19	63%	64	98	65%
US	49	112	43%	8	14	57%

Converting from initiation to completion

Demographic factors for students who had started the workshop, were also tested for association with successful completion of the workshop. Most demographic factors, including gender, race and ethnicity, student age (e.g., traditional vs nontraditional), English familiarity, graduation year, and parent/guardian educational level did not show any association with completion of the workshop (Figure 6). However, the remaining two factors, citizenship, and primarily language, did show a weak association with completion of the workshop. Interestingly, non-US citizen participants were more likely to complete the workshop than their US citizen peers despite the course being offered from the U.S. Similarly, participants whose primary language was not English were more likely to complete the workshop than their peers whose primary language was English. The relationship between citizenship and primary language factors was examined using a chi-square test of independence. The relation between these variables was significant, X^2 (1, $N=133$) = 61.807, p <. 001.

To further probe the interaction between Citizenship and Primary Language, we constructed Table 3 showing the conversation rates, as percentages, from initiation in the workshop to completion of the workshop. As shown below, non-US citizens converted from initiators to completers at the highest rates, regardless of primary language. However, US citizens whose primary language was not English converted at a higher rate that US citizens whose primary language was English, and that rate was similar to the higher conversion rates of non-US citizens. This indicates the primary difference was lower conversion for US participants with English as their primary language compared to the other participant groups.

EVT offers possible explanations for the two correlated demographic factors, citizenship and primary language, that demonstrated an association with completion (Figure 7; Table 3). For example, students from outside the US may perceive the value of the workshop differently than US participants. To test this, the value scores for completers of US citizens were compared to non-US citizens. As shown in Table 4, non-US citizens reported higher

attainment value scores than their US citizen peers (i.e., 28% with score of 2 for non-US citizens versus 5% for US citizens), while the US citizens reported lower attainment value scores (i.e., 44% with score of 0 for US citizens versus 28% for non-US citizens). While more subtle, the pattern for intrinsic value scores was reversed with proportionally more US citizens reporting the highest intrinsic value score compared to their non-US citizen peers (i.e., 60% with a score of 2 for US citizens versus 49% for non-US citizens). The reported utility value scores tracked closely between these two groups. Since US citizens whose primary language was not English also converted at a higher rate than their US citizen peers whose primary language was English (Table 3), their value scores were also compared (Table 5) and followed similar patterns to those found between non-US citizens and US citizens (Table 4). For example, US citizen completers whose primary language was English reported lower attainment value scores and higher intrinsic value scores than their US citizen peers whose primary language was something other than English. Again, reported utility value for the two groups were similar.

Next, factors which contribute to students' expectancies were examined with respect to completion. Most factors did not show a significant association with successfully completing the workshop including completion plans, GPA, prior research experience, perceptions of online courses, scientific computing experience, and seismology self-efficacy (Figure 7). However, two factors did demonstrate a weak association with completion and are conceptually related. Participants who were majoring in geophysics were more likely to complete the workshop than their peers who were geoscience majors or non-geoscience majors. Similarly, participants who had previously completed a course in geophysics, were more likely to successfully complete the workshop than their peers who had not previously completed a geophysics course.

Finally, participants' utility value, intrinsic value, and attainment value scores were analyzed for association with completion of the workshop. As illustrated in Figure 8, none of the value factors showed a statistically significant association with completion. However, collectively utility values 3-5 had higher completion than noncompletion and utility values 0-2 had higher noncompletion than completion, though not a statistically significant linear relationship.
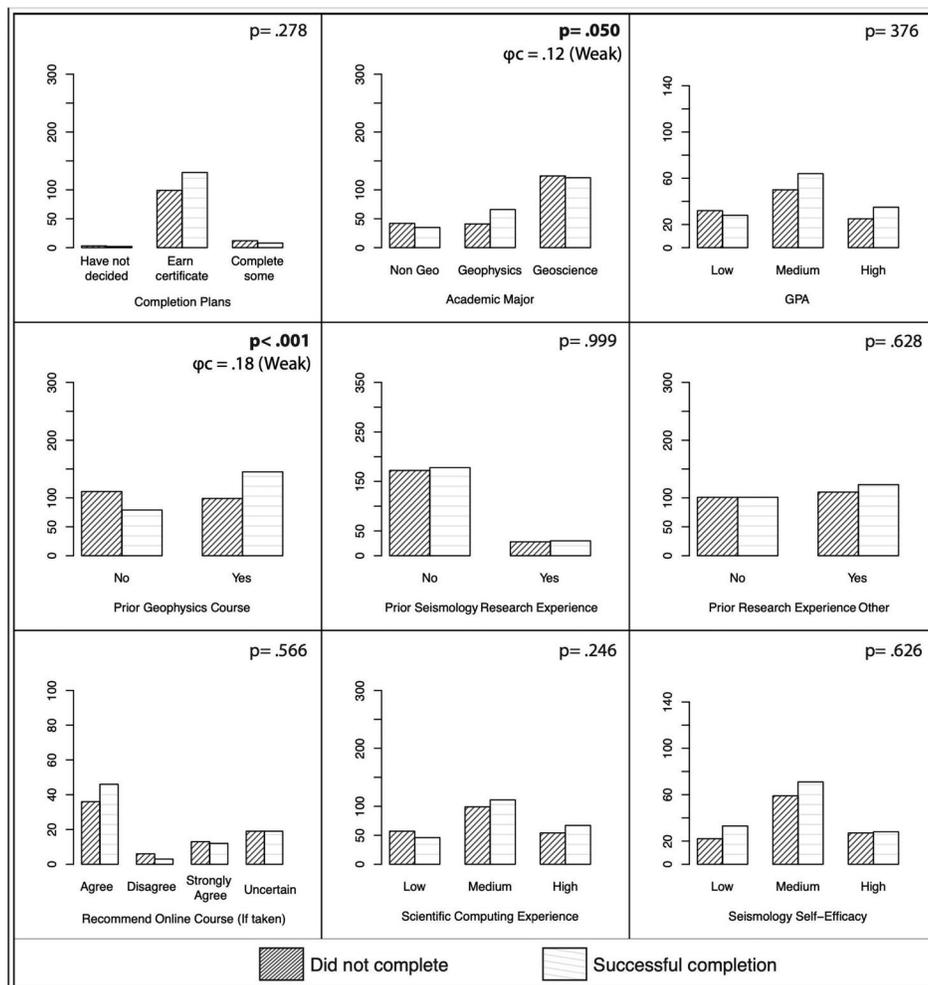
Figure 7. Associations between factors that align with expectancy, or students' current and future beliefs in their ability to be successful at a task. And whether students who initiated the workshop successfully completed the workshop (light shading) or not (dark shading). The number of participants for each factor is illustrated on the y-axis. Factors with a statistically significant association to registrants' initiation at ≤.05 level are highlighted in bold, with the strength of association φ_c shown.

Reasons for not initiating and/or completing the workshop

In addition to examining factors that had been identified as possible sources of motivation for students to initiate and complete the workshop, we also explored costs, or factors that might have negatively impacted students' motivation and persistence. We start with students who did not initiate, focusing on the question asking why they did not initiate. Not surprisingly, the participation rate for this population was extremely low with only six responses received from individuals out of the 26 total who had consented to participate and abandoned the course. The most frequently cited reasons included "The course required more time than I was able to dedicate", and "Personal reasons". Each was identified by three of the six respondents. The next most frequently cited reason was "I encountered too many technical difficulties with the software". This was cited by two of the six participants. Six other reasons were identified by at least one of the participants. These included the following reasons:

- The course did not align with the reasons I registered for the course.
- The English language of the course was challenging.
- The course required more effort than I anticipated.
- There was not enough support for my learning in the course.
- There was not enough interaction with the course instructors.
- There was not enough interaction with other course participants.

None of the respondents wrote in their own additional reasons for not starting the course.

A similar question was asked of participants who consented to participate and completed some but not all the workshop ($n = 84$). This group was asked to select one or more reasons why they did not complete the workshop from the same list (Figure 9) or write in additional reasons. Following a similar pattern, the two most cited reasons were that "The course required more time than I was able to dedicate", and "Personal reasons". The former was cited by nearly two-thirds of the respondents, while the latter was cited by just over half of the respondents. Twelve additional reasons were each cited by at least one participant. However, none were cited by more than 17% of the respondents.

Unlike the previous group, 41 participants wrote in their own reasons that they did not complete the workshop. In most cases ($n = 19$), these provided additional clarification to existing items they had also selected. For example, one respondent who selected that the course required more time than they were able to dedicate, also used the open-response option to clarify that they had "Started a full-time, in-person internship". Other respondents, however, did use the field to communicate reasons that were not included in the original list. Two new reasons, each with multiple respondents, were identified from the remaining data and indicated with an asterisk in Figure 9. These included finding it difficult to catch-up once they had fallen behind, and technical challenges beyond the workshop, such as loss of internet access or a laptop crash. The remaining five responses were added to a separate "Other" category that contained one-off or

Table 4. Number and percent of completers with the different value scores based on their citizenship.

Score	Attainment Value		Intrinsic Value		Utility Value	
	Non-US	US	Non-US	US	Non-US	US
0	21(28%)	25(44%)	11(14%)	6(10%)	0(0%)	0(0%)
1	34(45%)	29(51%)	28(37%)	17(29%)	1(1%)	0(0%)
2	21(28%)	3(5%)	37(49%)	35(60%)	8 (11%)	5(9%)
3	NA	NA	NA	NA	23(30%)	14(24%)
4	NA	NA	NA	NA	26(34%)	24(41%)
5	NA	NA	NA	NA	18(24%)	15(26%)

Table 5. Number and percent of US citizen completers with the different value scores primary language.

Score	Attainment Value		Intrinsic Value		Utility Value	
	English	Other	English	Other	English	Other
0	22(45%)	3(38%)	5(10%)	1(12%)	0(0%)	0(0%)
1	25(51%)	4(50%)	13(27%)	4(50%)	0(0%)	0(0%)
2	2(4%)	1(12%)	31(63%)	3(18%)	3(6%)	2(25%)
3	NA	NA	NA	NA	14(29%)	0(%)
4	NA	NA	NA	NA	21(43%)	3(38%)
5	NA	NA	NA	NA	11(22%)	3(38%)
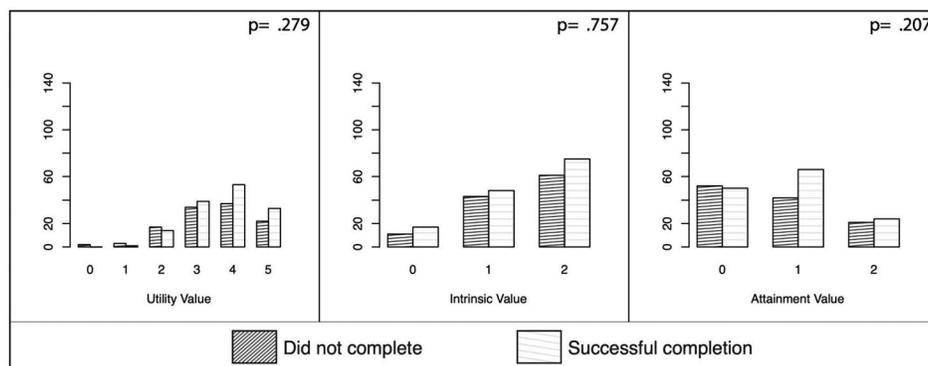
Figure 8. Students were asked to select reasons they registered for the workshop from a list. These reasons were grouped by value type; utility value (max = 5), intrinsic value (max = 2), and attainment value (max = 2). Association between value types and whether students who initiated the workshop successfully completed the workshop (light shading) or not (dark shading). The number of participants for each factor is illustrated on the y-axis. Value types with a statistically significant association to registrants' initiation at the ≤.05 level, are highlighted in bold with the strength of association φ_c shown.
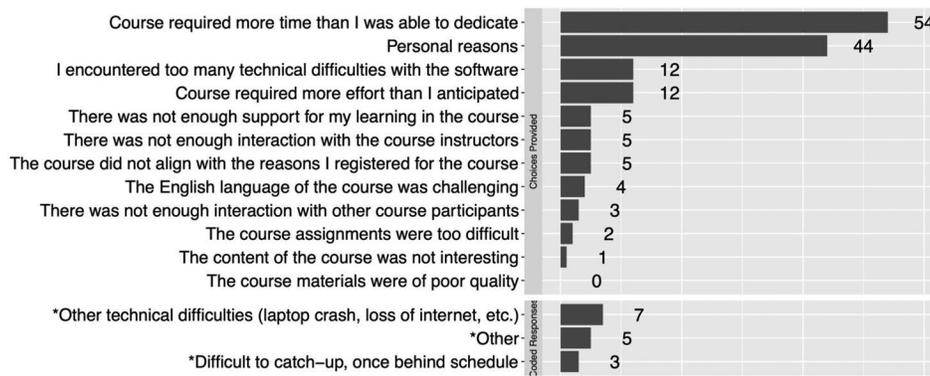
Figure 9. Reasons participants did not complete the SSB workshop and their frequency. Participants were allowed to choose all that applied or write-in their own reasons. *Indicates reason codes derived from respondents' "write-in" responses. (N = 84 Respondents).

nonsensical responses. For example, a one-off response includes "I'd recommend the number of quizzes lesser in each module", while a nonsensical response included "I should have completed the course".

Discussion

As noted previously, the evaluation of this workshop was not initially developed with the EVT in mind. Rather, survey items were developed based on the authors' experience working with students in similar courses and research experiences. When the data was collected and initially analyzed for associations with important outcomes (e.g., initiation and completion), the data showed complexity that did not immediately reveal clear trends. However, organizing factors according to demographic and EVT constructs, as presented above, allowed interesting and useful patterns to emerge in the workshop outcomes. The differing results for registration, initiation, and completion suggest that the contributions of expectancy, value, and cost to student motivation may decline, accumulate, and/or evolve from the beginning to end of the 14-week course. This aligns with Eccles and Wigfield's (2020) belief that the weighting of these major components of EVT varies across time and situation.

EVT posits that students' motivation to pursue different achievement tasks is determined most directly by their expectancies for success on the task and the extent to which they value the task (Wigfield et al., 2016, for review). For example, in the case of the SSBW it would be reasonable to assume that expectancy and value drive motivation when students register, as there is essentially no cost to the student. A student may see a workshop advertisement and decide that the workshop looks interesting and fun to them, aligns with their future goals, could help them make progress in their career path, and is something they believe they could successfully complete. Because the workshop is free and has no acceptance criteria such, as prior experience, demonstrated ability, or grades, students can be registered after a few mouse clicks and sharing some minor personal information.

As participants transition from registration to initiation, expectancy and value appear to continue driving motivation. As demonstrated in Figures 4 and 5, more than 50% of the expectancy factors and two-thirds of the value factors associated with initiation in the workshop. Expectancy factors showed both weak and moderate associations, while the value factors showed moderate and strong associations.

However, initiation is more complicated than registering. For example, registrants had to read and complete the steps necessary to successfully download a very large virtual disk (>7GB), install specialized software to mount the virtual disk on their personal computer, and follow additional steps to log into the LMS to initiate the first assignment. This workflow has several places where students might encounter challenges. Overcoming these challenges may come at the expense of other things that the student might do instead. In this way, small incremental costs may be incurred, with participants who encountered challenges accumulating more costs than those who did not encounter challenges or encountered fewer of them. This notion of accumulating costs aligns with work by Rosenzweig et al. (2020) who found that perceived costs increased across the semester for students in a college physics course.

Simultaneously, participants' expectancies or values may also be impacted during this transition to initiation. For example, those who encounter challenges and struggle to resolve them might begin to question how successful they can be in the workshop which would negatively impact their expectancy. Conversely, students who encountered only minor difficulties and successfully overcame them may see reward in learning how to run a new operating system on their computer for their own personal uses. In turn, such experiences may increase their perceptions of the workshop's value. Indeed, numerous studies at the college level have shown that value interventions have improved students' interest and course performance (e.g., Canning et al., 2018; Harackiewicz et al., 2016; Hulleman et al., 2010).

The transition from initiation to completion might increasingly be explained through a balancing of expectancy, value, and cost. Figure 7 above indicates that less than a quarter of the expectancy factors showed even weak associations with completion. Of note is the lack of association between the expectancy factor "Completion Plans", despite using an identical survey question and scale as Reich (2014), who did find associations with completion of MOOCs. Similarly, none of the value factors had a statistically

significant association with completion (Figure 8). It might be tempting to surmise that this lack of association with completion stems from non-completers simply deciding the workshop was not for them or that the workshop and materials were of inferior quality. However, an analysis of workshop participant perceptions found that even non-completers were satisfied with the workshop (71%) and described the workshop as high quality (92%) (Brudzinski et al., 2021). This aligns well with work by Wigfield et al. (2017) who proposed that when students perceive significant cost associated with a task their overall valuing of the task decreases. This combination in turn reduces the likelihood that students will continue in STEM courses (Barron & Hulleman, 2015; Wigfield et al., 2017).

While attainment and intrinsic values did not associate with completion for all the participants collectively (Figure 8), non-US participants and US citizen participants whose primary language was other than English both appear to perceived the workshop as more important to their self-concept or identity, which includes career identity, than their comparable peers. Conversely, US citizens whose primary language was English appeared to perceive a greater likelihood of enjoyment or satisfaction from engaging with the workshop than the rest of their peers. This may mean that both attainment and intrinsic value are positive motivators for initiation (Figure 5), but that intrinsic value may not be strong enough of a motivator to positively influence completion for a 14 week-long workshop. Unfortunately, the underlying reasons for these differences in reported values are not discernable from the current data available and is something to explore in future work.

Finally, EVT suggest that an accumulation of costs by participants further explain the observed completion/ non-completion results. Wei et al. (2024) found cost was a moderator in the relationship between attitudes, learning engagement, and perceived learning outcomes in MOOCs. Perez et al. (2019) also found negative association between costs and learning outcomes but in an on-campus rather than MOOC context. However, the weighting and role of perceived cost to influence academic outcomes is thought to vary in individuals and contexts (Eccles & Wigfield, 2020; Perez et al., 2019). Based on the different associations from initiation to completion, costs may also vary over time and in some cases become cumulative. For example, some costs identified in Figure 9, such as medical issues (e.g., influence of COVID) or technical difficulties (e.g., hard drive failures) appear to be acute and severe enough to immediately lead to course abandonment. Other costs such as a perceived lack of time or personal reasons, which likely include things that students did not do because of their initial participation in the SSBW, may accumulate over the duration of the workshop. This accumulation may outpace any positive changes to expectancy and value beliefs, and thus could also lead to workshop abandonment. It is important to note that these costs are not likely to be evenly experienced by all participants for a range of reasons. For example, factors such as socioeconomic status (e.g., access to stable high-speed internet), access to health care, and access to technical support, may insulate some from incurring costs. The demographic

results do not point to specific student groups having worse outcomes than others. However, this could be related to the sensitivity and focus of the data collection tools employed. For example, despite the international audience, language or cultural difficulties were not written in as reasons that students did not persist, though it is possible that the English-only survey was self-selecting.

The results suggest that completion of this free, open-access summer workshop for STEM majors may be driven through a balancing of accumulated costs versus expectancy and value. For example, a student who completed the workshop despite starting with low expectancy and value beliefs may have faced low costs or those beliefs increased over the course of the summer to prevent the costs from overcoming the expectancy and value. On the opposite end of the spectrum, a student who did not complete the workshop despite high initial expectancy and value beliefs may have accumulated high costs or experienced a decrease in their expectancy and beliefs value (e.g., the workshop is too demanding) for the costs to exceed the perceived benefits. Thinking about the relationship of expectancy and value with cost in this way for similar online courses may be particularly important as costs are inherently difficult to measure as those who are experiencing cost in a significant way may also be less likely to participate in evaluations.

In addition to factors that can be categorized through the EVT lens, four demographic factors also showed a weak association with initiation and an additional two demographic factors showed a weak association with completion. However, from the data collected as part of this study, it is difficult to determine why each of these demographic factors showed associations. It is possible that some of these factors may be proxies for costs, but there is not enough information available to adequately evaluate this. For example, non-traditional students may have initiated at a rate that was lower than their traditional peers (Figure 3), because they may have more competing factors on their time (e.g., family or work commitments, etc.). Other demographic factors may be associated with practical constraints. For example, students who reported that they were not at all familiar with the English language were less likely to initiate the workshop (Figure 3). Such students may have been able to register for the workshop successfully but may have found reading technical instructions more difficult when it came time to initiate the assignments. However, we do not find this trend extends to completion, as participants whose primary language was English completed at a rate that was lower than students whose primary language was something other than English. We do find evidence (Tables 4 and 5) that students from outside the US may perceive the value of the MOOC workshop differently than US participants.

It is also notable that factors such as gender, and race and ethnicity did not have any association with either initiation or completion of the course. This suggests equal access to the workshop, and an absence of biases and other factors that might have prevented some groups from succeeding once in the course. This is consistent with the earlier finding that the percentages of women and URM students from the United States completing the SSBW are greater than those receiving geoscience degrees annually (Brudzinski et al., 2021).

Limitations

Like all studies, there are several important limitations of this work that must be considered. First, while the overall response rates to the survey were strong, it was not consistent across all populations. For example, students who registered for the workshop but did not actually initiate the workshop had a very low response rate. As a result, their perspectives may be underrepresented here. Additionally, the design of the survey was limited to only those students who consented to participate and were motivated enough to complete the surveys. Therefore, the views of some groups of students may not be fully represented due to the bias induced by using surveys.

Next, the evaluation instruments were not designed, from the outset, to explicitly examine student motivation through the lens of EVT. As a result, the internal reliability of some of the items may be compromised; items included in the analysis may not measure the entirety of each construct category that they have been assigned (see supplemental material). In some cases, this may explain why we see only weak associations between factors and the student outcomes. Of particular concern in terms of assessment is the construct of cost. This represents a very broad construct and may be under-defined by the sample as those who encountered the largest costs may be least likely to engage with evaluation. Additionally, some costs may be more important than others. In this study, the evaluation item measuring costs was focused on capturing the range of costs students encountered rather than their relative importance to one another.

Next, the analysis of this data employed a rather simplistic, single-variate approach that does not capture complex interactions between groups of factors. Additionally, the analysis commonly binned together responses. While useful for an exploratory investigation, it does also blunt the investigation by overly simplifying things into broad categories. Therefore, some nuances and relationships within the data may have been lost in the process.

Finally, an important consideration is that the workshop ran during the depths of the pandemic when many other opportunities for students were canceled. Therefore, it is not clear how representative the population of registrants is and how representative their experiences and values are when compared to a normal year. For example, one concern was that more students may have been driven to the workshop because of the loss of other opportunities. However, enrollments in the SSBW have been similar in 2021 and 2022, suggesting that student interest in the workshop was not specific to the pandemic. Nevertheless, what students valued and the costs they encountered may have been impacted by the stress and external time demands induced by the pandemic.

Implications

It is anticipated that this workshop will continue through at least 2024, and this initial evaluation offers important insights for both future implementations of the Seismology Skill Building Workshop as well as for other STEM disciplines who are considering open-access, online workshops to teach scientific skills. This work establishes EVT as an important lens to both examine and re-design elements of the workshop with the goal of maximizing participant motivation and persistence. It also guides the further development of assessments to measure the workshop's impact on learners.

With regards to the workshop design, these results, along with recent efforts by others to test EVT based interventions (Rosenzweig et al., 2020; Rosenzweig et al., 2022), suggest that enhancing student motivations to pursue the workshop may be achieved. This would likely occur through a combination of strategies designed to nourish students' expectancy and value beliefs, while also mitigating real or perceived costs whenever possible. For example, future iterations of the workshop could incorporate resources that highlight how past participants have benefited from successfully completing the workshop. This might include a detailed tutorial describing resume building strategies to feature the workshop and the skills gained, ranging from computational (e.g., using Python packages such as Obspy) to more personal ones (e.g., self-motivation and discipline required to complete an ~70-h workshop that was not for credit). Additionally, interventions such as motivational messaging could be designed to target the needs of various subgroups such as the value differences highlighted in Table 4 and 5 above. Such efforts have been previously shown to enhance participants' utility values (e.g., Gaspard et al., 2015; Hulleman et al., 2010), as well as competency-based beliefs (Brisson et al., 2017; Canning & Harackiewicz, 2015; Rosenzweig et al., 2022), which in turn have contributed to enhanced STEM student performance (e.g., Canning et al., 2018; Harackiewicz et al., 2016; Rosenzweig et al., 2022).

Efforts to mitigate real costs by defining pinch points in the workshop where students encounter unnecessary or avoidable costs, and reducing students perceived costs both offer promise. For example, a major hurdle many students faced at the outset of the workshop was the need for fast internet with stable and consistent connection to support the download of a large (<7GB) virtual machine and technical knowledge to install software that occasionally required manipulating the computer BIOS. The virtual machine was required to create the common computing environment necessary to support the workshop's pedagogy. Cloud based computing environments may eliminate these costs as they would not require installations and should limit the need for such a robust internet connection. Additionally, since all computing would occur virtually, it may also increase accessibility for students with Chromebooks and tablets; students with these devices were excluded in 2020 due to the need for local computational power. To address these issues, a cloud-based solution was implemented in the 2022 SSBW.

Increased communication about costs may also be helpful to reduce students' perceptions of the workshop's psychological costs. For example, experience with the 2020 workshop should provide facilitators with significantly more accurate time estimates required to complete the workshop. This could help set more accurate student expectations and enable

students to employ better time management strategies. Additionally, including examples of other students overcoming costs could help to decrease participants' negative perceptions of costs. This was a benefit recently shown when students in a college level physics course read and evaluated examples of how students experienced and overcame costs of the course (Rosenzweig et al., 2020). It also showed an increase in self-perception of competence that indicated raised expectancy as well.

Another important implication for future workshops is to consider strategies for improving the evaluation of the workshop. After going through this process, we would change the completion threshold from the 100% used in this study to 80%. Such a change would more closely align "success" in this workshop considering successful students attend most but not all classes in a traditional course and few complete every assignment. It would also align more closely to other MOOCs which typically report completion rates as a percentage of registrants that simply passed the course (Jordan, 2020). This influenced our evaluation as participants' completion was used to determine which end-of-the-workshop survey students received. Lowering the threshold would have increased the number of students receiving the more robust survey provided to completers, including those who may have overcome more costs.

Finally, it will be important to align the overall evaluation with EVT from the outset. This should include revising and expanding survey items to ensure that each construct is adequately sampled and has a robust content validity. Leveraging existing assessments (e.g., Dietrich et al., 2017; Kosovich et al., 2015) either in their entirety or with modification as applicable will greatly help in this regard. This will be especially important for value constructs or costs that, as described above, may have been under sampled in this current work. In addition, employing different approaches to the data collection, such as reducing the survey length and exploring incentivizing responses may increase the number of students who did not complete the workshop in the evaluation dataset (Abdelazeem et al., 2023).

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