NSF INCLUDES National Network
Broadening Participation, Expanding Opportunities in STEM

NSF INCLUDES Alliances: Progress Addressing the Design Elements

Overview

According to an April 2022 survey conducted by the NSF INCLUDES Coordination Hub, NSF INCLUDES Alliances—especially those with two or more years of funding—have made significant progress in operationalizing critical aspects of the National Science Foundation's (NSF) design elements of collaborative infrastructure. This issue brief presents survey results using projects (as opposed to respondents) as the unit of analysis. It also provides background information about NSF INCLUDES, the survey used to collect process data from projects funded or co-funded by NSF INCLUDES, and the technical approach used to generate project-level composite scores.

NSF INCLUDES and the Design Elements of Collaborative Infrastructure

NSF INCLUDES (Inclusion Across the Nation of Communities of Learners of Underrepresented Discoverers in Engineering and Science) is a comprehensive national initiative designed to enhance U.S. leadership in discoveries and innovations by focusing on diversity, inclusion and broadening participation in Science, Technology, Engineering and Mathematics (STEM) at scale. A distinguishing feature of NSF INCLUDES is the use of the design elements of collaborative infrastructure, a process by which partner organizations (1) engage their community to formulate a shared vision of what can be accomplished collaboratively; (2) provide a platform for collaborative action; (3) develop common goals, objectives, metrics, and data collection procedures to measure shared progress and inform decision making; (4) develop structures across partner organizations to enhance coordination, communication, and visibility; and (5) establish the capacity for the expansion, sustainability, and scaling of their shared efforts. Each NSF INCLUDES Alliance uses this framework to accelerate its efforts to address systemic barriers to diversity, equity, and inclusion in STEM.

Source: https://www.includesnetwork.org/about-us/what-we-do

NSF INCLUDES Coordination Hub's Collaborative Infrastructure Survey and Analysis

The Hub's Collaborative Infrastructure Survey is designed to collect information about the progress that NSF INCLUDES-funded projects are making to address specific features of the design elements of collaborative infrastructure. The survey also serves as a resource for partnership projects seeking to define and measure their efforts to establish a cohesive infrastructure. In addition, the individual projects that participated in the survey can use their own data to assess their progress and inform their decision making.

Nine of the thirteen Alliances participated in at least one administration of the survey (the others opted out because they administer similar surveys). Respondents include key stakeholders (e.g., PIs, Co-PIs, staff, partners, researchers, and evaluators) who are in a position to assess their initiative's progress regarding the design elements. Over the past two years, the response rate among Alliance respondents is 65.6 percent (representing 219 of the 334 individuals who were asked to complete the survey), with some respondents completing the survey in multiple years.

To generate the statistics presented in this issue brief, we used item-response theory and confirmatory factor analysis to create Alliance-level composite scores for each survey item. This allowed us to assess the extent to which Alliances have operationalized specific features of the design elements. In addition, by disaggregating scores by years of funding received, we were able to compare results for newer and more mature Alliances for each of the design elements (Table 1), as well as for individual items (Tables 2a -2e). The technical approach, provided at the end of this document, presents the methodology used to generate these findings.

Key Findings

How to interpret the data. Table 1 provides Alliance-level composite scale scores for each of the design elements, while Tables 2a – 2e provide Alliance-level responses for individual items (by design element) from the Collaborative Infrastructure Survey. The results provided on these tables represent the overall standardized scale score obtained from the item-response theory and confirmatory factor analysis. Each score has a range of 1 to 100—with 100 representing the highest possible score (i.e., all respondents within a project answered the highest response category—either "achieved" or "strongly agree"—for a given item). The tables also provide the minimum and maximum Alliance-level standardized scale score responses (in parentheses and *italics)*. Finally, the tables provide overall results for each design element or survey item, as well as for number of years of Alliance funding.[1]

Findings for each of the design elements. As shown in Table 1, overall Alliance-level responses were highest for the design features associated with Leadership & Communication (82.7, on a scale of 1 to 100) and Shared Vision (81.2). Responses were lowest for the design features associated with Expansion, Sustainability & Scale (60.1). By the end of their second year of funding, Alliances reported higher scale scores as they matured in their efforts to operationalize the design elements—with Goals and Metrics and Expansion, Sustainability & Scale exhibiting higher gains in composite scores. This finding suggests that it takes Alliances 1-2 years to establish the foundations of a cohesive collaborative infrastructure.

Item-specific findings. Tables 2a – 2e provide Alliance-level responses for individual items on the Collaborative Infrastructure Survey. The following findings are worth noting:

- ***Shared Vision:*** Overall, scale scores were relatively high (86.0 or higher) for the two items pertaining to the process of developing project goals (Table 2a). In fact, the scale scores for these two items were quite high at the end of the first year of NSF INCLUDES funding, suggesting that the establishment of project goals was one of the first areas that Alliances addressed. Conversely, the scale score for having a project plan that addresses systemic barriers to broadening participation in STEM was relatively lower (71.4), suggesting that Alliances perceived more work was needed in the development of such a plan.
- ***Partnerships:*** As shown in Table 2b, overall scale scores were highest for the sufficiency of partners' composition to achieve project goals (82.5) and the presence of plans specifying partners' roles (78.6). Survey results provide evidence that several years are needed to prepare a plan that specifies partners' roles—with the scale score for this milestone being higher in Year 4 (83.7) than Year 1 (69.3). However, the scale score pertaining to the sum of partners representing the diversity of participant populations was *lower* in Year 4 (71.0) compared with Year 1 (84.4). This may help to explain why, as Alliances mature, they report adding new partners to address specific needs—with scale scores higher in Year 4 (70.8) than Year 1 (53.3).
- ***Goals & Metrics:*** By the end of Year 1, the scale score for partners' involvement in making sense of shared measures data was relatively high (78.0) and was even higher in Year 4 (81.1) (Table 2c). Scale score for the other three items were also higher as Alliances gained experience in their shared measures work. Most notably, the scale score for using data to make regular improvement was 71.5 in Year 4 (compared with 49.1 in Year 1), suggesting that mature Alliances were better positioned to use shared measures to inform their strategic planning and decision making.
- ***Leadership & Communications:*** Overall scale scores were relatively high (84.3 or higher) for the four items that focus on the structures required to harness partners' expertise and optimize opportunities for collaboration (Table 2d). However, even for mature Alliances (i.e., those in their fourth year of funding), scores were low for three areas that are harder to achieve—having project decisions informed by input from the participant population (76.5), having core partner regularly seeking advice from one another (74.6), and having internal procedures the minimize power imbalances among partners (74.6).
- ***Expansion, Sustainability, & Scale:*** As shown in Table 2e, the scale score for having a strategic vision of what activities will be sustained was lower in Year 4 (69.4) than Year 1 (73.9). However, scale scores for other sustainability items were higher over time. For example, by the end of Year 4, the scale scores for having a written sustainability plan and securing project funding were 66.7 and 56.2 respectively—suggesting that mature Alliances had made progress in their efforts to expand and scale their work.

Taken together, these findings reveal areas where mature Alliances are most likely to report having made progress over time, and areas where more work is needed to operationalize specific features of the design features.

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[1] In theory, one would expect that more mature Alliances (i.e., Alliances with more years of NSF INCLUDES funding) would report more progress around the operationalization of a given design element. However, it is possible that respondents' perspectives concerning their accomplishments (or the progress they still need to make) around a given design element shift as they recognize the complexity of a given issue—with respondents realizing more work is needed to fully achieve a given feature as they begin to delve more deeply into a particular task. In addition, the composition of respondents taking the survey within a given Alliance may change over time.

Table 1. Overall Alliance-level scores for the design elements of collaborative infrastructure

Design element	Overall *(n=9 projects)*	Number of years of funding as an NSF INCLUDES Alliance			
		1 year *(n=3 projects)*	**2 years** *(n=3 projects)*	**3 years** *(n=6 projects)*	**4 years** *(n=3 projects)*
Shared Vision	81.2 *(66.4, 89.2)*	75.7 *(66.4, 86.1)*	82.3 *(79.2, 87.2)*	83.1 *(77.5, 89.2)*	81.7 *(76.1, 86.5)*
Partnerships	74.5 *(59.4, 89.3)*	68.2 *(59.4, 78.8)*	74.9 *(70.5, 80.2)*	77.7 *(64.3, 83.1)*	73.3 *(63.6, 89.3)*
Goals & Metrics	71.7 *(54.5, 90.9)*	59.9 *(54.5, 68.3)*	73.4 *(65.9, 82.1)*	74.9 *(59.4, 85.6)*	75.5 *(71.6, 90.9)*
Leadership & Communication	82.7 *(67.2, 94.2)*	77.2 *(68.0, 84.1)*	89.0 *(85.3, 94.2)*	83.9 *(67.2, 94.2)*	78.7 *(73.4, 86.8)*
Expansion, Sustainability & Scale	60.1 *(43.3, 83.2)*	48.4 *(43.3, 53.5)*	62.5 *(61.1, 64.9)*	62.3 *(48.0, 70.6)*	66.4 *(57.2, 83.2)*
Overall (Across all design elements)	77.1 *(61.6, 87.2)*	70.2 *(61.6, 78.1)*	80.2 *(76.5, 86.4)*	79.1 *(67.5, 86.9)*	76.4 *(70.3, 87.2)*

NOTE: The score for a given design element represents the overall standardized scale score obtained from the item-response theory and confirmatory factor analysis. Each score has a range of 1 to 100, with 100 representing the highest possible score, i.e., all respondents within a project answered the highest response category (either "achieved" or "strongly agree") for a given item. In addition, we provide the minimum and maximum project-level standardized scale score response *(in* parentheses and *italics)*.

Table 2a. Item-specific Alliance-level scores for Shared Vision

Survey item	Number of years of funding as an NSF INCLUDES Alliance				
	Overall *(n=9 projects)*	**1 year** *(n=3 projects)*	**2 years** *(n=3 projects)*	**3 years** *(n=6 projects)*	**4 years** *(n=3 projects)*
Our project's goals are informed by an assessment of the participant population's needs	87.2 *(73.6, 96.7)*	87.0 *(73.6, 94.2)*	86.2 *(76.5, 96.7)*	89.5 *(81.3, 96.4)*	83.8 *(75.0, 91.7)*
All of our core partners are involved in the process of developing our project's goals	86.0 *(68.8, 91.7)*	80.3 *(68.8, 89.6)*	88.4 *(85.9, 90.9)*	87.3 *(81.3, 91.7)*	86.4 *(80.8, 91.1)*
Our project has a plan that addresses systemic barriers to broadening participation in STEM	71.4 *(52.9, 80.4)*	62.5 *(52.9, 75.0)*	74.3 *(68.8, 79.2)*	72.3 *(64.1, 80.4)*	75.7 *(71.2, 79.2)*

NOTE: The score for a given survey item represents the overall standardized scale score obtained from the item-response theory and confirmatory factor analysis. Each score has a range of 1 to 100, with 100 representing the highest possible score, i.e., all respondents within a project answered the highest response category (either "achieved" or "strongly agree") for a given item. In addition, we provide the minimum and maximum project-level standardized scale score response *(in* parentheses and *italics)*. Items are sorted from highest to lowest for Overall score. Finally, the calculation of project-level scores excluded six items that were only asked of respondents who were in a position to provide information about the status of project work within their *own* partner organization. As such, Tables 2a-2e do not include these six items.

Table 2b. Item-specific Alliance-level scores for Partnerships

Survey item	Number of years of funding as an NSF INCLUDES Alliance				
	Overall *(n=9 projects)*	**1 year** *(n=3 projects)*	**2 years** *(n=3 projects)*	**3 years** *(n=6 projects)*	**4 years** *(n=3 projects)*
The sum of our core and supporting partners represent the range of institutions needed to achieve our project's goals	82.5 *(65.6, 95.8)*	80.8 *(65.6, 89.3)*	80.5 *(79.2, 82.4)*	84.7 *(81.8, 91.7)*	81.8 *(67.3, 95.8)*
Our project has a plan that clearly specifies each partner's role	78.6 *(56.9, 95.8)*	69.3 *(56.9, 87.5)*	80.7 *(67.3, 92.9)*	79.7 *(64.3, 89.3)*	83.7 *(67.9, 95.8)*
The sum of our core and supporting partners reflect the diversity of our participant population	77.0 *(50.0, 93.8)*	84.4 *(73.6, 93.8)*	76.7 *(72.2, 81.3)*	76.3 *(52.1, 86.9)*	71.0 *(50.0, 83.9)*
Our project adds new partners to address a given need (e.g., to access crucial expertise and/or additional participants)	66.4 *(51.5, 83.3)*	53.3 *(51.5, 56.3)*	66.6 *(64.5, 70.0)*	70.5 *(54.2, 78.6)*	70.8 *(54.2, 83.3)*

NOTE: The score for a given survey item represents the overall standardized scale score obtained from the item-response theory and confirmatory factor analysis. Each score has a range of 1 to 100, with 100 representing the highest possible score, i.e., all respondents within a project answered the highest response category (either "achieved" or "strongly agree") for a given item. In addition, we provide the minimum and maximum project-level standardized scale score response *(in* parentheses and *italics)*. Items are sorted from highest to lowest for Overall score. Finally, the calculation of project-level scores excluded six items that were only asked of respondents who were in a position to provide information about the status of project work within their *own* partner organization. As such, Tables 2a-2e do not include these six items.

Table 2c. Item-specific Alliance-level scores for Goals & Metrics

Survey item	Number of years of funding as an NSF INCLUDES Alliance				
	Overall *(n=9 projects)*	**1 year** *(n=3 projects)*	**2 years** *(n=3 projects)*	**3 years** *(n=6 projects)*	**4 years** *(n=3 projects)*
All of our core partners are involved in the process of making sense of findings that emerge from the project's analysis of shared measurement data	80.2 *(67.3, 91.7)*	78.0 *(67.3, 85.0)*	81.0 *(78.3, 82.5)*	80.5 *(75.0, 85.7)*	81.1 *(73.1, 91.7)*
Our project has participatory processes to refine its measures, indicators, metrics, and/or data collection methods	73.0 *(47.9, 95.8)*	56.6 *(47.9, 66.7)*	71.2 *(61.5, 78.3)*	76.8 *(69.6, 82.1)*	83.4 *(73.2, 95.8)*
Our project has the capacity to track progress across all partners (e.g., protocols, common metrics)	66.7 *(50.0, 84.1)*	55.5 *(52.3, 58.3)*	66.8 *(52.5, 77.8)*	69.0 *(50.0, 84.1)*	73.3 *(59.6, 83.3)*
Our project uses data to make regular improvements	65.2 *(43.8, 91.1)*	49.1 *(47.4, 50.0)*	67.6 *(52.1, 85.0)*	68.8 *(43.8, 91.1)*	71.5 *(59.6, 87.5)*

NOTE: The score for a given survey item represents the overall standardized scale score obtained from the item-response theory and confirmatory factor analysis. Each score has a range of 1 to 100, with 100 representing the highest possible score, i.e., all respondents within a project answered the highest response category (either "achieved" or "strongly agree") for a given item. In addition, we provide the minimum and maximum project-level standardized scale score response *(in* parentheses and *italics)*. Items are sorted from highest to lowest for Overall score. Finally, the calculation of project-level scores excluded six items that were only asked of respondents who were in a position to provide information about the status of project work within their *own* partner organization. As such, Tables 2a-2e do not include these six items.

Table 2d. Item-specific Alliance-level scores for Leadership & Communication

Survey item	Number of years of funding as an NSF INCLUDES Alliance				
	Overall *(n=9 projects)*	**1 year** *(n=3 projects)*	**2 years** *(n=3 projects)*	**3 years** *(n=6 projects)*	**4 years** *(n=3 projects)*
Our project's leadership structure leverages the collective knowledge of partners and other stakeholders	88.7 *(70.8, 100.0)*	88.3 *(75.0, 97.7)*	93.5 *(88.9, 100.0)*	88.4 *(70.8, 98.2)*	85.1 *(78.6, 95.8)*
Our project leadership is willing to engage in frank and open discussions when areas of disagreement exist	86.9 *(59.1, 100.0)*	85.8 *(77.9, 90.9)*	92.3 *(88.6, 96.7)*	87.0 *(59.1, 100.0)*	82.5 *(79.2, 85.7)*
Our project leadership provides opportunities for building relationships across partners	86.5 *(70.8, 98.2)*	78.2 *(72.2, 83.3)*	92.2 *(88.6, 95.0)*	88.1 *(70.8, 98.2)*	85.9 *(79.2, 91.1)*
Our project leadership has structures in place to encourage full participation by all partners	84.3 *(66.7, 96.7)*	82.4 *(67.1, 90.4)*	91.0 *(87.5, 96.7)*	83.7 *(66.7, 92.9)*	80.8 *(78.8, 83.3)*
All of our core partners collaborate with each other to align their actions	80.7 *(65.3, 94.6)*	74.4 *(65.3, 80.8)*	87.1 *(80.9, 92.9)*	82.4 *(66.7, 94.6)*	77.2 *(67.3, 87.5)*
Our project's decision-making processes are transparent to those inside the project	80.4 *(61.1, 95.0)*	74.6 *(61.1, 81.8)*	87.3 *(79.5, 95.0)*	80.1 *(68.8, 87.5)*	79.9 *(69.6, 87.5)*
Our project's decisions are informed by input from our participant population (e.g., through representation by members of the participant population on a steering committee)	79.6 *(53.8, 92.5)*	75.4 *(60.9, 84.1)*	84.1 *(77.8, 89.6)*	81.0 *(62.5, 92.5)*	76.5 *(53.8, 90.0)*
All of our core partners regularly seek advice from one another (e.g., effective strategies for addressing a given challenge)	79.5 *(65.4, 98.1)*	74.6 *(67.3, 79.5)*	85.1 *(77.9, 95.0)*	81.5 *(68.8, 98.1)*	74.6 *(65.4, 83.3)*
Our project has internal procedures that minimize power imbalances among partners	77.5 *(54.7, 90.0)*	71.9 *(54.7, 81.8)*	84.2 *(75.0, 90.0)*	78.4 *(62.5, 89.3)*	74.6 *(68.8, 80.0)*

NOTE: The score for a given survey item represents the overall standardized scale score obtained from the item-response theory and confirmatory factor analysis. Each score has a range of 1 to 100, with 100 representing the highest possible score, i.e., all respondents within a project answered the highest response category (either "achieved" or "strongly agree") for a given item. In addition, we provide the minimum and maximum project-level standardized scale score response *(in* parentheses and *italics)*. Items are sorted from highest to lowest for Overall score. Finally, the calculation of project-level scores excluded six items that were only asked of respondents who were in a position to provide information about the status of project work within their *own* partner organization. As such, Tables 2a-2e do not include these six items.

Table 2e. Item-specific Alliance-level scores for Expansion, Sustainability, & Scale

Survey item	Number of years of funding as an NSF INCLUDES Alliance				
	Overall *(n=9 projects)*	**1 year** *(n=3 projects)*	**2 years** *(n=3 projects)*	**3 years** *(n=6 projects)*	**4 years** *(n=3 projects)*
Our project has a strategic vision of what activities will be sustained beyond the current award period	72.2 *(47.7, 85.7)*	73.9 *(69.6, 76.9)*	76.3 *(70.5, 83.3)*	70.7 *(47.7, 85.7)*	69.4 *(53.8, 81.3)*
Our project contributes to the field's knowledge base about effective strategies for broadening participation in STEM	69.8 *(44.4, 87.5)*	54.7 *(44.4, 61.4)*	68.6 *(63.5, 72.2)*	73.7 *(62.5, 78.6)*	78.5 *(71.2, 87.5)*
Project has a written plan that outlines a strategy for sustaining activities beyond the current award period	55.1 *(39.6, 75.0)*	48.6 *(43.8, 52.1)*	52.6 *(46.9, 56.3)*	53.8 *(39.6, 66.7)*	66.7 *(50.0, 75.0)*
Project has secured funding beyond the current award period	43.6 *(26.7, 79.2)*	32.6 *(26.7, 42.5)*	37.9 *(32.5, 43.8)*	45.5 *(33.3, 57.1)*	56.2 *(41.7, 79.2)*

NOTE: The score for a given survey item represents the overall standardized scale score obtained from the item-response theory and confirmatory factor analysis. Each score has a range of 1 to 100, with 100 representing the highest possible score, i.e., all respondents within a project answered the highest response category (either "achieved" or "strongly agree") for a given item. In addition, we provide the minimum and maximum project-level standardized scale score response *(in* parentheses and *italics)*. Items are sorted from highest to lowest for Overall score. Finally, the calculation of project-level scores excluded six items that were only asked of respondents who were in a position to provide information about the status of project work within their *own* partner organization. As such, Tables 2a-2e do not include these six items.

Technical Approach

The remainder of this document summarizes the technical approach used to construct composite scores for the Hub's Collaborative Infrastructure Survey. Specifically, it (1) provides a brief overview of scaling methodologies; (2) describes the rationale for using scaling to develop composite survey scores; (3) clarifies the terminology associated with scaling; and (4) provides a description of data included in the analysis and a detailed description of processes used. All of the analysis performed here is done with R version 4.0.3 with the following packages: readxl, writexl. ltm, psych, lavaan, and semPlot.

Overview of Scale and Scaling

Scaling is a device to measure attributes of interest and is used to provide quantitative information about these attributes. Most of us are familiar with scales and we use them on a daily basis. For example, scales such as time, temperature, height, weight, and speed are very familiar in the physical world—with devices providing numbers that represent universal "quantities" or scales that convey properties for attributes of widespread interest.

Social science scales are quite different. Perception, intelligence, satisfaction, opinion, or achievement are complex and often abstractive constructs, where the attributes of interest are generally not directly visible or measurable. Quantifying these constructs through use of a single indicator is difficult, and often requires measurement through multiple observable indicators. For example, students' responses on a survey about attitudes toward science may be indicators of their engagement in STEM. Similarly, measuring students' mathematical skills requires observing what students can do on mathematical assessments that contain multiple domains—e.g., single-digit addition, multi-step arithmetic, arithmetic with vulgar fractions, etc. (Wu & Adams, 2007).

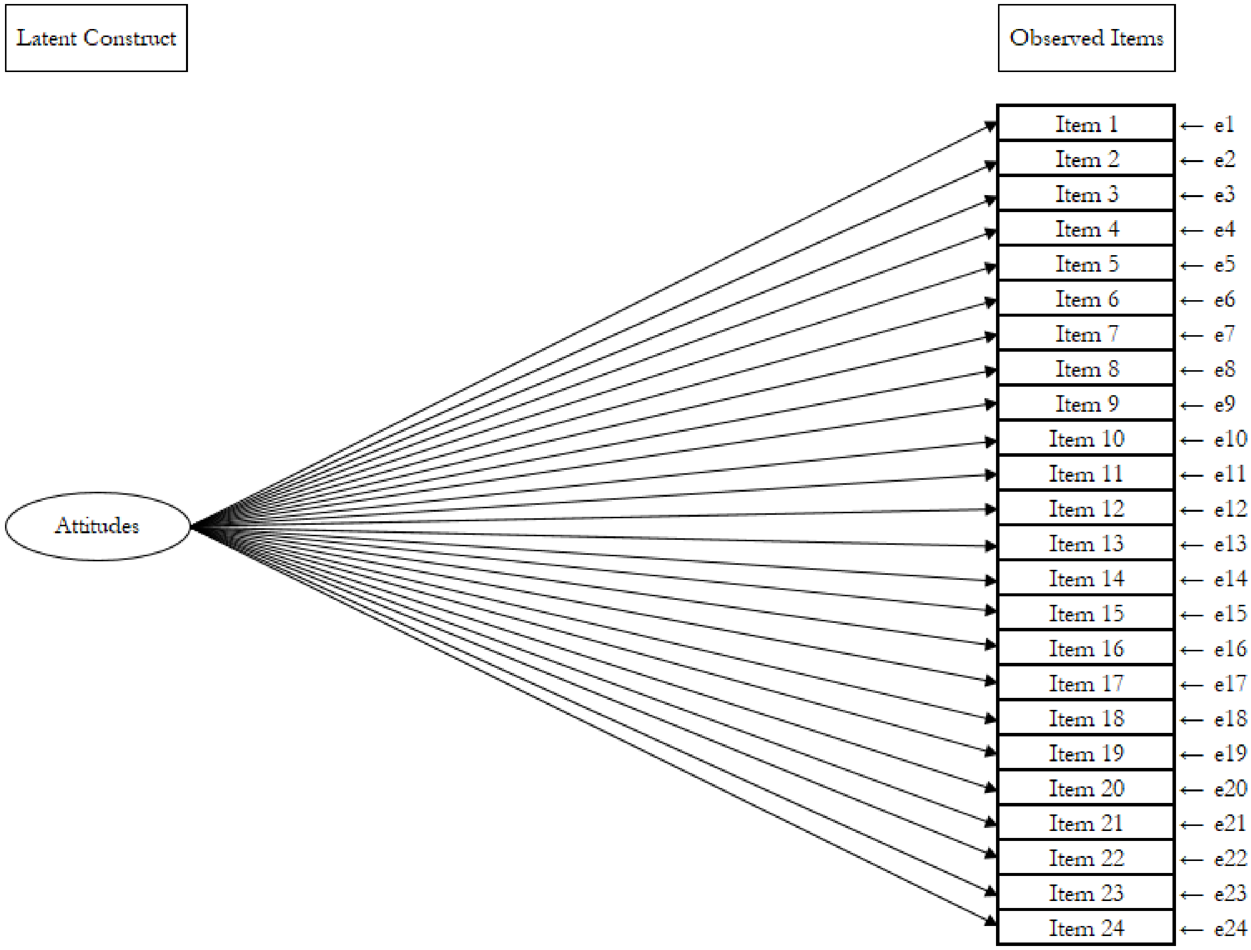
As such, social science scales often deal with concepts that are not directly visible—therefore latent—and the attribute of interest cannot be directly quantified from one indicator. Rather, they must often be measured by collecting information on multiple indicators that are associated with a given attribute. Measuring a complex construct by examining multiple-observable indicators is generally referred to as "scaling," requiring the application of mathematical models such as item-response theory (IRT) and/or Confirmatory Factor Analysis (CFA). Such mathematical models help to test theories, evaluate a construct's validity of indicators, build the construct with the validated indicators, and quantify measurement (Shultz & Whitney, 2005).

Rationale for Scaling

Two primary rationales for using scaling are: (1) testing a theory and evaluating construct validity; and (2) assessing the relationship between a latent construct and observed items to test reliability and scale accuracy (to quantify the attribute of interest). The following scenarios illustrate the rationale for using scaling techniques.

Evaluating Construct Validity. The scaling can be used to examine the extent to which survey items contribute to an overall finding. As a part of a high school initiative designed to increase participation in STEM, you are asked to use a 24-item survey to assess students' perceptions about specific science topics. In this situation, the construct you want to measure is "attitudes toward science for each student" and you hypothesize that such attitudes vary across the 500 students. While the attitudes toward science topics is an abstract construct that cannot be measured directly, you theorize that the construct can be quantified through the 24 survey items. Figure 1, which illustrates a latent approach for addressing this question, represents a graphical presentation of how the survey sets out to measure students' attitudes—with each item response (i.e., each observed item) and overall scaling of items reflecting a given student's outlook (i.e., positive or negative) about science.

Figure 1. Latent model to measure STEM engagement among of 500 students



The arrows indicate the relationship between the latent construct and observed items, with the attitudes toward science determining the likely responses to each survey item. The direction of the arrows is extremely important, since it illustrates that students' attitudes are not determined by the items (rather, students' attitudes influence the likelihood of their item responses). The figure also illustrates that there are levels of errors associated with each observed item.

Another way to explain the relationship between the latent construct and observed items is that the latent construct is the cause, and the item responses are the effect, where the item responses are understood as a consequence of the latent construct. In this example, the scaling approach allows for testing the latent model, provides vital information about the appropriateness of the theoretical model and facilitates efforts to evaluate the construct validity and relationship among items. The scaling approach also allows for an estimation of the measurement error for each item and provides precise information about how much (or little) each item accounts for the latent construct.

Testing Reliability and Accuracy. A scale can be reliable (but not accurate) if it measures a construct very consistently—but is consistently providing the wrong numerical values. Likewise, a scale can be accurate (but not reliable) if it generates the right numerical values in an inconsistent manner. Reliability in scaling is how repeatable a measurement is, while accuracy is how close a value is to its true value. For example, to assess the reliability of a reading exam, a teacher might administer the same test twice to examine whether student-specific results are similar or differ over time.

Finally, researchers should not use simple composite scores to make comparisons across survey participants. As shown in Table 3, three students who took a survey might have a simple composite score of 17 (even though they responded to the survey uniquely) and there is no way to assess how much (or little) each item accounts for the latent construct. Because the scaling approach assesses the relationship between a latent construct and observed items (as shown in Figure 1), researchers can obtain the weights that indicate the contribution of each item. The scale scores from this approach will be generated by multiplying the item response by the weights. The scores from this approach provide accurate scores that place each individual at the precise location (as shown in the scale score column in Table 3).

Table 3. Survey responses, simple score, and scale score

Respondent	Item 1	Item 2	Item 3	Item 4	Item 5	Simple composite score	Scale score
A	5	4	2	3	3	17	7.5
B	1	5	3	3	5	17	6.0
C	5	2	5	2	3	17	8.1

NOTE: In this example, each of five questions were asked with a 5-point Likert scale response option, and we assume these five items are normally distributed with reasonably high correlations (i.e., Cronbach's alpha = 0.8). The simple score is based on the sum of raw survey responses, while the scale scores are generated by multiplying the item responses by the weights.

Terminology

Dimensionality. In scaling, checking the dimensionality is important (e.g., in IRT, it is assumed that a construct is unidimensional and the covariance among the items can be explained by one underlying construct). Dimensionality can be checked by examining the eigenvalues from the principal component analysis (PCA). The PCA explores the underlying variance structure of a set of correlation coefficients and identifies patterns in the set of correlation coefficients. The eigenvalues can be used to condense the variance in a correlation matrix—the patterns with the largest eigenvalue have the most variance and so on, down to factors with too small or negative eigenvalues that are usually ignored (Hambleton et al., 1991). Often the PCA of this type suggests that a set of items may represent multiple dimensions as there are eigenvalues greater than 1 (Loehlin, 1987).

Local independence. Checking the local independence is also critical in the scaling. Many approaches assume that a response to an item is independent of a response to other items in a latent model (Kline, 2005; Reeve, 2007). This can be tested by examining the fit statistics and assessing the variances of error terms from the confirmatory factor analysis (CFA). (Hambleton, 1983; Baker, 2001; Kline 2005).[2]

Eigenvalue. A commonly used criterion for the number of factors to rotate is the eigenvalues-greater-than-one rule proposed by Kaiser (1960). Eigenvalues are the linear algebra concepts that we need to compute from the covariance matrix in order to determine the PCA of the data. The PCA represents the directions of the data that explain a maximal amount of variance. Eigenvalues are simply the coefficients attached to give the amount of variance carried in each Principal Component. The PCA hypothetically examines all possible number of factors from the input data.

MI. Nearly all scaling analyses impose some kind of restrictions on the parameters to be estimated. The model chi-square test reflects the extent to which these imposed restrictions impede the ability of the model to reproduce the means, variances, and covariances that were observed in the sample. The MI is the X^2 value, with 1 degree of freedom and MI reflects the improvement in a model fit that would result if a previously omitted parameter were to be added and freely estimated. It is not uncommon in practice for researchers to consult MIs to suggest model modifications that lead to a "better" fitting model.

Chi-square (X^2). The chi-square statistic compares the size of any discrepancies between the expected results and the actual results, given the size of the sample and the number of variables in the relationship. A chi-square (X^2) statistic in scaling is a test that measures how a model compares to actual observed data and provides information about "badness-of-fit." X^2 does not have a particular range and the interpretation of value depends on specific degrees of freedom in a model but the higher its value, the worse the model's correspondence to the data; and significant P-values indicate poor fit.

RMSEA. Since X^2 is often influenced by the sample size, RMSEA is often used to ensure the model fit. It is a measure of goodness of fit for statistical models, where the goal is for the population to have an approximate or close fit with the model. The RMSEA ranges from 0 to 1, with smaller values indicating better model fit. A rule of thumb is that RMSEA smaller than 0.05 indicates a good fit (Kline, 2005).

[2] Two types of fit statistics used are: Chi-square (X^2), and Root Mean Square Error of Approximation (RMSEA). X^2 in scaling context provides information about "badness-of-fit." X^2 does not have a particular range and the interpretation of value depends on specific degrees of freedom in a model but the higher its value, the worse the model's correspondence to the data; and significant P-values indicate poor fit. Since X^2 often influence by the sample size, RMSEA is often used to ensure the model fit. The RMSEA is similar to X^2 in a sense that it provides "badness-of-fit," and a rule of thumb is that RMSEA smaller than 0.05 indicates good fit (Kline, 2005).

Data and Methods Used in the Analysis of the Collaborative Infrastructure Survey

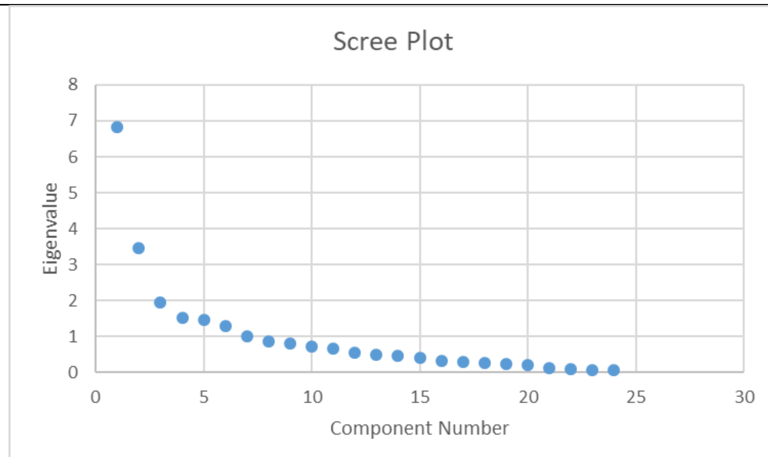
Data for this scale analysis were derived from the Coordination Hub's Collaborative Infrastructure Survey. The survey contains 24 items[3] to assess projects' progress on implementing the NSF INCLUDES design elements of collaborative infrastructure—including Shared Vision; Partnerships; Goals & Metrics; Leadership & Communication; and Expansion, Sustainability & Scale.

A total of 88 respondents from six Alliances responded to the survey. Respondent type includes PIs/Co-PIs, project leadership, project members, researcher, evaluators, and consultants. The composition of respondent types differ across projects. Based on the skewness and kurtosis statistics, data have reasonably normal distributions—i.e., skewness ranges from -1.803 to 1.338, and kurtosis ranges from -0.8995 to 2.986. We did not impute missing data and we used the full information maximum likelihood estimator in the analysis.[4,5]

Assessments of Dimensionality and Local Independence. As indicated previously, checking the dimensionality and local independence is important and provides vital information for the rest of the scaling process. To check the dimensionality, we examined eigenvalues with the PCA. The eigenvalues provide the amount of variance in the total sample accounted for component (e.g., factor) and the PCA examines the variance in each component model.[6] Table 4 shows the eigenvalues and scree plot from the PCA. In this particular data, for example, a single component yielded an eigenvalue of 6.819 that is accounted for 28 percent of the underlying variance structure of a set of correlation coefficients. As stated previously, the PCA suggests that a set of items may represent as multiple dimensions as there are eigenvalues greater than one and the data showed the possible seven components (i.e., seven sets of covariance patterns exist in the data).

Table 4. Eigenvalues and Scree Plot examining the dimensionality and local independence

Total variance explained			
	Initial Eigenvalues		
Component	Total	Percent of variance	Cumulative percent
1	6.819	28.414	28.414
2	3.459	14.413	42.827
3	1.945	8.105	50.932
4	1.508	6.284	57.215
5	1.446	6.024	63.239
6	1.276	5.317	68.556
7	1.006	4.191	72.747
8	0.857	3.572	76.319
9	0.801	3.337	79.655



This was followed by a CFA for further examination of local independence and construct validity. This initial single-factor model also showed a poor fit in the CFA model with $X^2_{(252)}$ = 494.8, and RMSEA = 0.148. Further, the analysis indicated statistically significant interdependency among error terms of several items. Based on these results, the 24 items of the scale were multi-dimensional, and we used the CFA analysis with the MI to further examine the covariance structure among error terms and improve the fit.[7,8,9]

Modification of the Model. The above findings are not surprising (i.e., the interdependency of error terms) since nearly all latent models impose some kind of restrictions on the parameters to be estimated. To determine which restrictions to relax (so the fit statistics will be improved), we generated the MI statistics. Since the MI provides an approximate amount of X^2 decrease when a

[3] While the survey includes 30 items, we excluded six items that were only asked of those respondents who were in a position to provide information about the status of project work within their *own* partner organization.
[4] The lavaan package provides case-wise, full information maximum likelihood estimation if the data meets either missing completely at random (MCAR) or missing at random (MAR).
[5] In estimating the standard errors, the lavaan will automatically switch to the weighted least square estimator if data do not have any missing data and the "ordered" argument is used. In our analysis, this option was not implemented.
[6] The PCA hypothetically examines all possible number of factors from the input data.
[7] If the scale is determined to be unidimensional, we planned to analyze data with Graded Response Models that are adequate for ordinal responses (Reeve, 2007).
[8] CFA relies on the regression type equations and can model with the error, compared to the IRT.
[9] Typically, the scaling analysis involves a step to perform either Multi-Sample Analysis or Differential Item Functioning test. This test is to examine the group invariance of the scale—i.e., sometimes groups, such as defined by respondent type, have different probabilities of endorsing a given item on a multi-item scale. When this occurs, the scale score will be artificially higher or lower values. We did not perform this step, as such an analysis would require a larger sample size.

particular constraint is released, one can use the MI to identify the constraint(s) that has the large MI values and make re-parameterization of the model (Jöreskog & Sörbom, 1996). The model chi-square test reflects the extent to which these imposed restrictions impede the ability of the model to reproduce the means, variances, and covariances that were observed in the sample. To avoid overfitting the model, we released constraints sequentially, each time assessing the statistical significance of the X^2 change in fit (Byrne, 1991). In our data, we repeated the MI processes 28 times. We observed no statistically significant difference between the 27th and 28th models. Therefore, we selected the 27th model as the final model. Figure 2 shows the visual representation of both the initial and final models for easy comparison.

Computing weights for each survey item and project level score. Once the final model was established, we estimated the weights of each item with the completely standardized solution. In this solution, both latent and observed variables are standardized. We then calculated individual respondent scores by multiplying the item response with the standardized coefficients. Therefore, the scales were weighted by the proportion of items the scale contributed to the factor. The respondent-level scores can be used as-is or can be aggregated at the project level. Further, the scores can be used in other analyses such as regressions. For further analysis, we standardized the scale scores on a range of 0 to 100, with 100 representing the highest possible score. Table 5 presents the unstandardized coefficients, standard errors, standardized coefficients for each item, and fit statistics for the final model.

Figure 2. Visual representation of the model

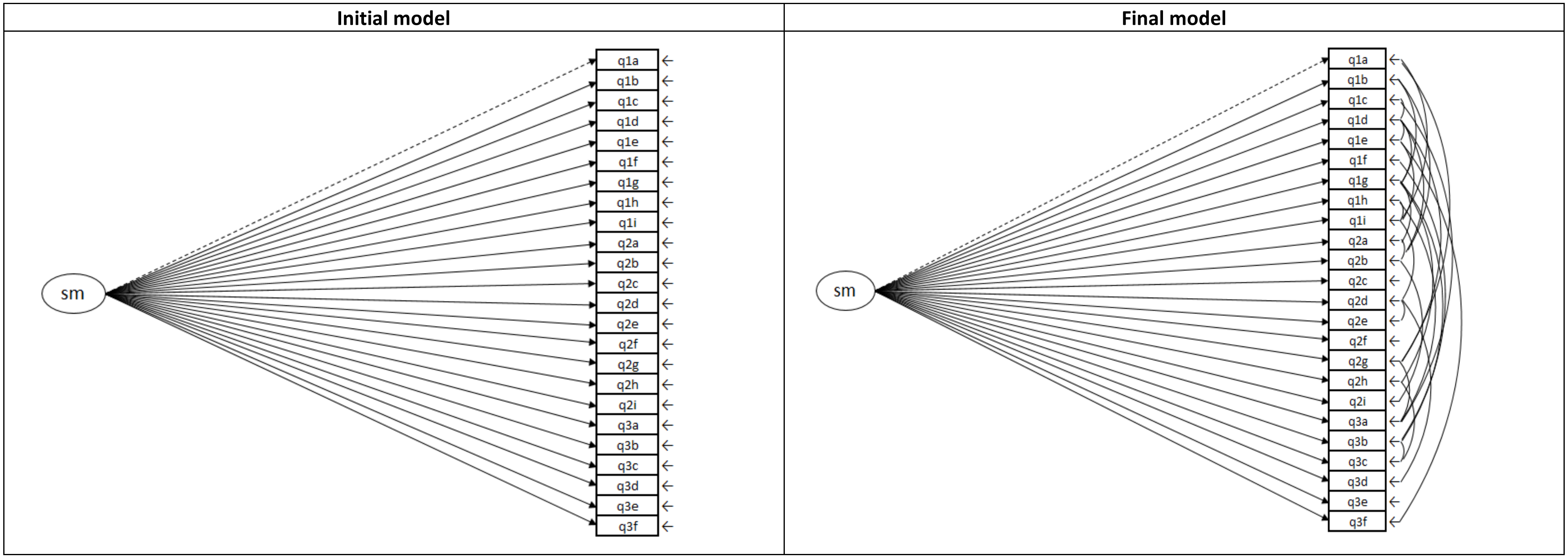


Table 5. Standardized coefficient and fit statistics

Item	Unstandardized coefficient	Standard errors	Standardized coefficient
Our project has a plan that clearly specifies each partner’s role	1.000	0.000	0.667
Our project has a plan that addresses systemic barriers to broadening participation in STEM	0.716	0.242	0.474
Our project adds new partners to address a given need (e.g., to access crucial expertise and/or additional participants)	0.957	0.249	0.635
Our project has participatory processes to refine its measures, indicators, metrics, and/or data collection methods	0.396	0.229	0.274
Our project has the capacity to track progress across all partners (e.g., protocols, common metrics)	0.066	0.216	0.047
Our project uses data to make regular improvements	0.624	0.222	0.447
Our project contributes to the field’s knowledge base about effective strategies for broadening participation in STEM	0.153	0.206	0.115
Project has a written plan that outlines a strategy for sustaining activities beyond the current award period	0.857	0.271	0.516
Project has secured funding beyond the current award period	0.130	0.212	0.101
Our project’s goals are informed by an assessment of the participant population’s needs	0.494	0.147	0.543
Our project’s leadership structure leverages the collective knowledge of partners and other stakeholders	0.638	0.169	0.621
Our project leadership has structures in place to encourage full participation by all partners	0.562	0.158	0.577
Our project has internal procedures that minimize power imbalances among partners	0.392	0.176	0.351
Our project leadership is willing to engage in frank and open discussions when areas of disagreement exist	0.433	0.188	0.364
Our project leadership provides opportunities for building relationships across partners	0.805	0.177	0.764
Our project’s decision-making processes are transparent to those inside the project	0.506	0.227	0.417
Our project’s decisions are informed by input from our participant population (e.g., through representation by members of the participant population on a steering committee)	0.676	0.211	0.517
Our project has a strategic vision of what activities will be sustained beyond the current award period	1.022	0.273	0.611
All of our core partners are involved in the process of developing our project’s goals	0.718	0.187	0.638
All of our core partners are involved in the process of making sense of findings that emerge from the project’s analysis of shared measurement data	0.718	0.187	0.627
All of our core partners collaborate with each other to align their actions	0.705	0.201	0.569
All of our core partners regularly seek advice from one another (e.g., effective strategies for addressing a given challenge)	0.718	0.186	0.635
The sum of our core and supporting partners represent the range of institutions needed to achieve our project’s goals	0.636	0.241	0.420
The sum of our core and supporting partners reflect the diversity of our participant population	0.559	0.268	0.327
			Fit Statistics
			X2: 304.0 **Df:225** **RMSEA: 0.089**

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