J-STEM

Journal of Research in STEM Education

Vol 7, No 1, July 2021

j-stem.net

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Publisher / Founder : i-STEM / Gultekin Cakmakci
ISSN:2149-8504

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ISSN:2149-8504 (online)

Journal of Research in STEM Education
Vol 7, No 1, July 2021, 1-20
https://doi.org/10.51355/jstem.2021.94

RESEARCH REPORT

A Quantitative Analysis of a Customized Mentoring Program with STEM Underrepresented Students

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Abstract: *This article highlights a customized mentoring program that successfully supported underrepresented students in science, technology, engineering, and mathematics (STEM) disciplines at a university in the northeastern part of the United States (U.S.). Because of the national and regional needs to augment underrepresented, minority, first-generation, and low-income STEM college students, this study investigated efforts to expand the number and retain such population in higher education STEM programs through a customized mentoring program based on a National Science Foundation (NSF) grant. In particular, we evaluated the necessity of strong and broad-based mentoring characteristics using assessment tools and surveys. The study was conducted with 34 participants in STEM fields. The participants' motivation mean scores in STEM was measured at three different points in time (pre-, mid-, and end-year) and compared using descriptive statistics and repeated measures analysis of variance (ANOVA). Results obtained indicated significant improvement in mentoring characteristics such as goal orientation, resource management, and academic performance with mean scores ranging from 4.99 to 5.21. Although additional findings from the repeated measures ANOVA showed no statistically significant differences, however, the marginal mean scores suggest the customized mentoring program had some positive effect and the mentoring practices supported underrepresented groups toward successful navigation of STEM disciplines. We discuss the study limitations, implications, and future research directions.*

Keywords: *Customized mentoring, mentoring, STEM program, underrepresented students*

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To cite this article: Asempapa, R.S., Morales, A. W., Agili, S. S. (2021). A Quantitative Analysis of a Customized Mentoring Program with STEM Underrepresented Students. *Journal of Research in STEM Education*, *7*(1), 1-20. https://doi.org/10.51355/jstem.2021.94

ISSN: 2149-8504 (online)

Introduction

Underrepresented students in science, technology, engineering, and mathematics (STEM) disciplines, including females, receiving scholarships and mentoring are likely to succeed in STEM related disciplines in their college education (Doerschuk et al., 2016; Estrada et al., 2018). Comparing the difference between the participation of students in STEM and the real graduation rates in these fields, it is important to recognize the experiences and recent views of under-represented STEM students. Remarkably, only a few empirical studies addressed questions about how underrepresented STEM scholars navigate their educational careers and remain motivated throughout their professional endeavors. (Estrada et al., 2016; Hernandez et al., 2013; Tyler-Wood et al., 2018). In addition, the graduation rates among under-represented university students in most STEM fields are low (National Science Foundation [NSF], 2010).

According to Crisp and Cruz (2009), mentoring is an outstanding and successful way to help and encourage the success of college students and has a great beneficial aspect for students as they transfer from college to work. Enhanced academic performance, social integration and retention rates are among the major benefits of mentoring STEM undergraduates (Mangold et al., 2002). For underrepresented minorities and first-generation college students, especially women in STEM disciplines, being a part of a trustworthy or credulous mentoring relationship is critical. (Tsui, 2007). Quantitative evaluations of mentored STEM students have shown that mentoring positively influences and shapes scientific identity as mentors link students to career resources and research opportunities, provide emotional support, foster students' confidence and self-efficacy in science, and help them value scientific research (Atkins et al., 2020; Byars-Winston et al., 2015; Estrada et al., 2018). Because mentoring has been identified as an effective and beneficial component of STEM underrepresented college students' success (Fifolt & Abbott, 2008; Fifolt & Searby, 2010) this research study became necessary and centered on a customized mentorship approach for underrepresented groups.

Significance of the Study

Mentoring has been recognized and grown over the past few decades as an important and productive educational model to empower and encourage college STEM students in their early career growth (Atkins et al., 2020; Garcia-Melgar & Meyers, 2020). Research studies and literature reviews have associated mentoring with several positive results for apprentices ranging from self-reported well-being and comfort to unbiased performance metrics (Estrada et al., 2016; Hernandez et al., 2013; Jacobi, 1991). Many scholars have recognized and established mentoring as a promising and capable approach to tackle the absence of diversity in STEM-related fields (Hernandez et al., 2018; Lunsford, 2016). Moreover, undergraduate underrepresented groups tend to gain from a mentor's direction and guidance by contributing to scientific research, discoveries, scientific identity, and innovations (Hernandez et al., 2018). Therefore, in this study, we add to the growing literature on mentoring under-represented STEM students who achieve the highest level of academic achievement and their career aspirations.

Recent research has shown positive impacts, outcomes, and access to various forms of mentoring STEM undergraduate college students (Estrada et al., 2016; Hernandez et al., 2018). This reflects a documented and understood need to identify and expand on mentoring relationship characteristics that are helpful to STEM underrepresented undergraduate students. Accessibility of such mentoring programs is crucial, and it is important to pay more consideration to mentors and mentees' characteristics (Crisp & Cruz 2009). By examining the measurable, theoretical, and practical nature of mentoring interactions in a customized NSF STEM mentoring program, we highlight the advantages of this type of mentoring and expand on the work of other research studies. In this regard, we examined underrepresent college STEM students mentoring characteristics including goal orientation, instrumental, and socioemotional abilities using statistical and quantitative analyses. Therefore, we carried out this research study to investigate participants' motivation score in STEM at three different points in time (pre-, mid-, and end-year) and report on the quantitative analyses to provide evidence of a customized mentoring model effectively applied in STEM fields with underrepresented students.

Background and Related Literature

Jacobi (1991) has defined successful and productive mentoring to consist of five main elements: (a) a connection or association based on accomplishment or acquisition; (b) it includes care and sustenance, direct assistance, and character modeling; (c) it has reciprocal advantages; (d) the relationship configuration is personal; and (e) in the mentoring environment mentors become experts and impact achievement. Mentoring is the basis for exploring the essential aspects of the individuality and social adaptation of students and their assimilation into college as a group (DuBois et al., 2002) and delivers an important and effective supportive network for students who are underrepresented in STEM fields (Summers & Hrabowski, 2006). Therefore, we developed an undergraduate STEM mentoring program using an empirical-based approach to explore the core components that affect the impact of a customized model of mentoring for underrepresented STEM students.

The important factor about the nature of this research is the conviction that mentoring with a customized approach has the potential to upsurge the achievement of college students with deprived experiences. In this research study, our theoretical framework is based on a customized mentoring program. Research studies on mentoring show that mentoring underrepresented undergraduate students are likely to get better grade point averages (GPAs), excellent graduation rates, and successful professional options in STEM disciplines (Summers & Hrabowski, 2006). According to Nikolova Eddins and William (1997), under the "apprenticeship model" most undergraduate mentoring programs function by matching a qualified, knowledgeable, and accomplished professors as mentors—a more seasoned or experienced individual—with a student mentee—a less experienced junior colleague (i.e., the traditional model [TM]). However, most research studies have acknowledged the shortcomings of the TM mentoring in STEM fields for undergraduate college students (Eby et al., 2000; Feldman et al., 2013; Kobulnicky & Dale, 2016).

The weaknesses, inadequacies, and limitations of the TM mentoring approaches warrant the development of alternatives to fill this gap, because even well-trained, knowledgeable, competent, and experienced mentors can find themselves unsuspectingly in a relationship that is dysfunctional. For these reasons, our commitment and contribution to the field of mentoring, and coupled with the aim of this article was to examine, explain, and share the impact of a customized mentoring model (CMM) for underrepresented STEM students in an NSF scholarship program. Our CMM has some similarities with other community mentoring approaches but is different from the TM of mentoring. Figure 1 below illustrates how the similarities and discrepancies between the TM and CMM are considered and interpreted.

This CMM paradigm avoids many of the drawbacks that are associated with the TM of mentoring and creates opportunities for entirely new beneficial outcomes to emerge. The CMM sees mentoring as personalized learning for STEM diversity and inclusion in ongoing academic and social support for diverse STEM students. The multidisciplinary nature and value of the CMM is that it creates an environment to facilitate student retention, timely degree completion, and career goal setting for underrepresented minority and female students. The constant pulse-checking mentors do with their mentees in the CMM, allows them to work with the faculty and mentee to customize tutoring and support based on the mentees' needs.

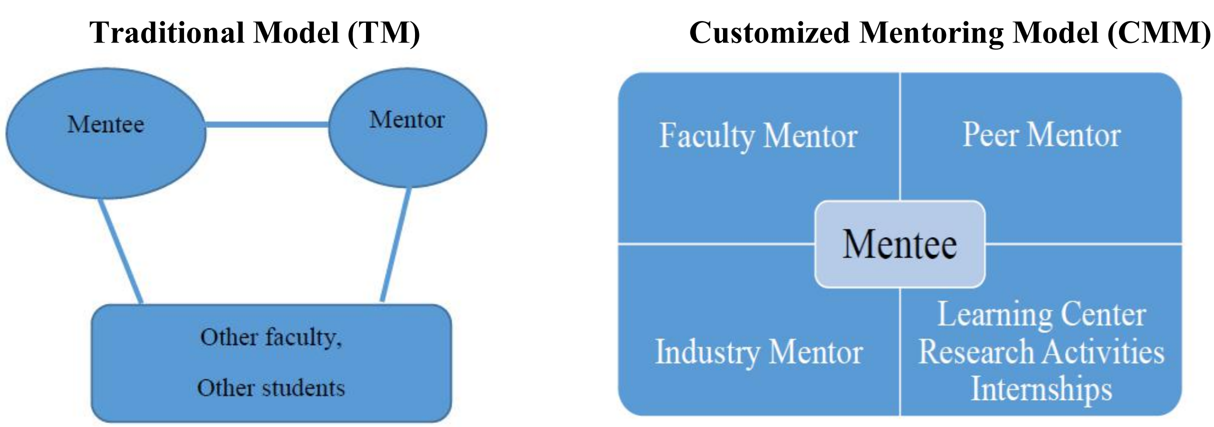

Figure 1. Mentoring models, left traditional model, right customized model

ISSN: 2149-8504 (online)

One strategy to assist STEM undergraduates in developing and promoting their scientific identities is through mentoring. So, we believe that through the CMM, student's development of scientific identity (i.e., general sense of self as a scientist) will improve their academic performance, retention and persistence in STEM, and STEM degree completion (Maton et al., 2016; Merolla & Serpe, 2013; Syed et al., 2011). In the next subheadings below, we describe in detail the essential characteristics and activities for each component of our CMM approaches.

Peer Mentoring

Research indicates that peer mentoring is an essential contributor to individual development in academic settings (Eby et al., 2008) and an effective and successful way to help students navigate through college and develop a productive career path (Morales et al., 2017; Kobulnicky & Dale, 2016). For this study, peer mentors were chosen by program chairs and other faculty members in STEM related fields, and we chose to use other STEM students from the Learning Center as peer mentors for our STEM scholars because those students have already received some training in mentoring. Within this customized mentoring program, we matched 15 freshman NSF STEM scholars with a peer mentor with the exact or identical major of the mentee. The peer mentorship groups and teams met on a month-to-month basis without the inclusion and involvement of the STEM faculty.

To develop, improve, and enhance the cohesiveness of the relationship between the mentees-mentors, we motivated and encouraged them to partake in the NSF STEM club events and other STEM related activities on campus. Some of the NSF STEM club activities included the following: (a) area science and engineering fair volunteering, (b) area science and engineering–award ceremony, (c) STEM career launch volunteering, and (d) NSF STEM club talk show on storm and pollutants in areas of water supplies. Additionally, the NSF-STEM club officers offered their services at a food bank through community service. Moreover, fundraising activities were organized, where strong participation was exhibited by recent mentees and other members.

Compared with other forms of mentoring, in a customized setting, peer mentors are capable to draw on more recent and reliable experiences to share with mentees, and mentees are usually more comfortable approaching peers for mentoring needs (Tenenbaum et al., 2014; Holland et al., 2012). Most of the literature on mentoring show that peer mentoring promotes academic, psychological, and career advancement in STEM fields (Anderson et al., 2019; Crisp et al., 2017). In particular, customized peer mentoring when designed effectively can and do impact learning in the STEM disciplines (Tenenbaum et al., 2014). Research studies have shown that college students who experience customized or near-peer mentoring show increase outcomes in program satisfaction and affective commitment to the university (Crisp et al., 2017; Holland et al., 2012). Tenenbaum et al. (2014) explained that customized peer mentoring supports mentees and mentors' development, incorporates established mentoring guidelines, and offers unique

ISSN: 2149-8504 (online)

opportunities for the integration of research and teaching in STEM disciplines. Moreover, customized peer mentoring model provides personal, educational, and professional benefits for mentees and mentors, enhances learning, and increases the interest and engagement of college students pursuing STEM disciplines (Kobulnicky & Dale, 2016; Thomas et al., 2015). Consequently, we believe the customized mentoring approach allows for students to serve as peer or near-peer mentors on projects, which enriches mentor experiences and contributes to many learning benefits and opportunities for peer mentors themselves (Holland et al., 2012; Sales et al., 2006).

Faculty Mentoring

Research suggests that faculty mentoring plays an important role in the learning and success of most college students (Chelberg & Bosman, 2019; Fifolt et al., 2014). In particular, faculty engagement with underrepresented STEM college students helped such students to develop effective working skills and grow as experts in their field. Through this customized mentoring program, we established a faculty-to-mentee mentoring strategy to assist the STEM scholar's engagement in the program. Each STEM scholar was matched with the most suitable or appropriate faculty mentor in the first semester of their first year. We deliberately included both men and women faculty mentors from diverse backgrounds and with varied expertise in STEM fields as supported by other studies (Gilmer & Martinez, 2014; Thomas et al., 2015). Other mentors if possible were included from areas closely related to the STEM scholars' field of study because they had wonderful rapport and relationship with the assigned scholar.

We aim at continuing the faculty mentoring component as part of our customized mentoring model for our STEM scholars in the coming years, and with only minor changes that we deem effective and appropriate. The faculty mentoring factor has continued to provide support, encouragement, and motivation for most of the STEM scholars. Additionally, we have proposed a plan that will give mentees the choice to change or self-select faculty mentors to promote and support strong relationships and collaboration, which we believe has the potential to improve or increase mentor-and-mentee relationships and appointments. Overall, the faculty mentoring program enhanced the self-esteem of the mentees, provided opportunities and resources for the STEM scholars, and brought about an increase in the academic achievement of the scholars.

Industry Mentoring

We believe industry mentoring provides college students with the opportunities to learn from experienced professionals and is an essential component for the STEM education. Additionally, industry mentoring helps college student broaden their network, advance their professional skills, and expand their insight of career opportunities. According to Veenstra (2014), industry

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mentoring is a backbone to STEM education, and it is the conduit for college students to successfully transition to a career in a STEM related field. Because industry mentoring supports STEM education, we purposefully linked our STEM scholars with industry mentors and invited knowledgeable industry speakers to campus to share their experiences with our scholars. We fully embraced the industry mentoring concept and STEM scholars had the opportunity to interact and learn from industry leaders or workers who had a better understanding of what was required to be successful in a STEM field.

The STEM scholars had the chance to visit companies and met with varied professionals and scientists with diverse backgrounds. The selection of industry mentors was based on their expertise, experience, skill set, and relevance to our STEM scholars. The industry mentors were mostly from firms, corporations, and establishments that were in partnership with our NSF-STEM programs. We expect the industry mentoring program to continue because of its effectiveness and relevance to our STEM scholars and the overall program. The continual commitment of the industry mentors sharing their time, knowledge, and experiences with the STEM Scholars has been priceless and extremely useful. This relationship with our industry partners, has provided the STEM scholars the opportunities for internships, connect or network with local companies, and occasionally securing full-time jobs after completing their programs. Other industrial mentoring activities included talks at different stages in the program.

Learning Center and Other Activities

Most mentoring programs do not operate independently or in silos but many of them share and collaborate on information and are interwoven with numerous academic and professional programs including learning centers (Pleschová & McAlpine, 2015; Tolbert, 2015). As a result, we decided to include the university learning center facility in our CMM for the STEM scholars. We solicited the help of tutors with careers in STEM fields and in the STEM tutoring-only group from the learning center for the mentoring program. The learning center was equipped with standard resources to engage the STEM scholars in various activities for their academic and professional growth. All the STEM scholars who engaged in the tutoring activities during the mentoring program met frequently with their tutors for at least a minimum of four sessions. During these tutoring sessions, some of the STEM scholars got the opportunity to learn about study skills and time management. Additionally, the learning center continued to offer workshops and seminars for the NSF-STEM scholars in special topics including students' readiness level, learning profiles, test preparation, and interests. Overall, the learning center activities or interventions and coupled with the mentoring program, had a positive impact on the STEM scholars by providing support to a wide range of academic enhancement, career opportunities in STEM fields, learning profiles, and personal accountability. In the next two

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subsections, we discuss the relationship between mentoring and retention, and the benefits of mentoring.

Retention and Mentoring

Research studies indicate that retention connects carefully to issues regarding students' perseverance, withdrawal, and attrition (Braxton et al., 2007). Based on the literature, one can define *retention* as incessant enrollment of students from one academic year to the other without any break (Braxton et al., 2007; U.S. Department of Education, 2010). Research shows that mentoring has the potential to be an effective tool and approach to boost the representation of STEM college students where systematic under-representation has happened. Additionally, prior research has revealed that mentoring enhances and promotes growth in underrepresented students in the areas of academic achievement, enrollment, and retention (Wilson et al., 2010). Designing programs to recruit and retain individuals into STEM majors in college, requires individual STEM identity, persistence, and institutional traits (Vincent-Ruz & Schunn, 2018). This is crucial because if one cannot see or perceive themselves in that capacity with such a character, then choices leading to a STEM career will be less likely, regardless of the motivating or engaging nature of STEM activities.

According to Fifolt and Searby (2010), completion rates for STEM and related degrees by students in the United States (U.S.) is expected or anticipated to be lower as compared to students in other countries. For this reason, it is important to attract and retain more diverse people (mentors) among economically disadvantaged STEM worker communities, so we can maximize invention, creativity, and competitive capacity of STEM mentees in the world. Moreover, it is essential and important for researchers to develop and engage students from diverse backgrounds and support their efforts through prescribed and recognized mentoring programs. The idea of specialized mentoring programs associates with improved retention rates of students seeking degrees in STEM fields (Packard, 2004). Therefore, engaging college underrepresent STEM students in the CMM is imperative and timely.

Benefits of Mentoring

Mentoring is a two-way street and can be described as a relationship involving mutual actions. Research indicates mentoring relationship promote growth and development in both mentors and mentees through the experiences and opportunities, and individuals without mentoring experiences demonstrate lower expectations and less satisfaction with their work. Several research studies allude to the importance and benefits of mentoring especially in college education and its effectiveness and positive impact on the educational achievement of minority undergraduates (Girves et al., 2005; Kendricks et al., 2013; Lunsford, 2016). Additionally, we agree that mentoring is a significant factor to the growth of an individual in an academic environment and the workforce (Carmel & Paul, 2015; Eby et al, 2008). Russell and Adams (1991) explained that mentoring is a strong and forceful relational mentor interaction with mentee, where the mentor offers guidance, support, and constructive criticisms concerning career paths and personal growth or development.

This relational exchange or discussion between the mentor and the mentee may include academic support, behavioral support, funding opportunities, skill-development, and participation in professional associations (Cargill, 1989). Research shows that mentors play a significant role in the lives of their mentees and this influential behavior usually have positive influence on the STEM identity of students (Robnett et al., 2018). Therefore, developing customized mentoring programs for underrepresented STEM students is important and cannot be over emphasized. For the past few decades, mentoring has shown to be an effective approach or strategy for guaranteeing student achievement in the areas of STEM (Carmel & Paul, 2015; Kendricks et al., 2013; Robnett et al., 2018). Mentoring is a strategic enterprise that provides mentees from underrepresented clusters with experience and the exposure to positive role models, supportive networks, and relational collaboration with knowledgeable professionals for their success.

Especially, a college setting is the perfect, central, and ideal place for STEM students during their academic career to observe and experience for the first time in their lives, role model relationships. Robnett et al. (2018) studied instrumental (task-based, skill-oriented instruction) and socioemotional mentoring (specific advice and assistance) relationships between mentors and mentees. Instrumental mentoring is task driven, and it includes assigning the mentee with certain skills and resources to progress in a particular situation. On the other hand, socioemotional mentoring pertains to the provision of interpersonal backing system for the mentee. Robnett et al. (2018) found that those mentorship relationship or types positively affected undergraduate college students academic and career paths. Moreover, strong positive effects were established between the mentor-mentee relationships on both instrumental and socio-emotional types of mentorships (Robnett et al. 2018).

Research Aim

The aim of this study was to explore a customized mentoring program with underrepresented undergraduate students in STEM fields that employed both instrumental and socioemotional techniques through peer mentoring, faculty mentoring, and industry mentoring. Because of the nature of our research design and data, the following research questions were examined:

Research question 1(RQ1). What descriptive information does the survey reveal about the NSF Scholars in this customized mentoring program?

Research question 2 (RQ2). Is there a difference in motivation of undergraduate STEM students between the before, during, and after conditions of the programs?

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Methodology

The aim of this study was to identify key and relevant factors that contribute to the achievement and success of under-represented STEM undergraduate students utilizing a custom mentoring model (CMM) in a mentoring program. Under our NSF STEM program, the STEM scholars were offered a three-prong mentoring environment: peer, faculty, and industry. One of the researchers developed a mentoring handbook for the three types of mentoring, which included mentor training. Students customized their mentoring by selecting the appropriate peer mentors, based on mentor backgrounds and demographics. Peer mentoring was highly encouraged by the researchers to ease the transition to college life, which is critical for incoming scholars.

Once the transition to college was successful, STEM scholars were asked to choose faculty and/or industry mentors. We focused on customized mentoring, more-specifically near-peer mentoring (Anderson et al., 2019; Holland et al., 2012; Tenenbaum et al., 2014), where slightly older students' mentor younger STEM scholars, in the critical first semester of college. Therefore, the methods utilized in this study were mainly on quantitative approaches that examined the experiences of underrepresented undergraduate STEM scholars from a customized mentoring program perspective.

The customized mentoring program was led by six STEM faculty members with diverse experiences and backgrounds and one administrative or supporting staff. The six faculty members specialty include electrical and computer engineering, electronic engineering, mathematics and computer science, civil engineering, mathematics education, and geosciences. Their contributions and tasks in the program included recruitment and retention plans, mentoring plans, STEM club and career activities, and tutoring programs. The NSF Scholars program was implemented at the beginning of the academic year to help the smooth transition of scholars throughout the first year of college.

Because of the customized nature of the mentoring program, each faculty member was matched with a STEM scholar majoring in an area closely related to the mentors' area of expertise and experience. On average, there were about four to five scholars being assigned to one faculty member. Throughout the mentoring program, activities that were emphasized included: (a) learning community practice—STEM scholars were required to register at least two courses with a peer mentee; (b) mandatory mentoring meetings—scholars were mandated to attend the usual monthly program meetings with their mentors; and (c) undergraduate research projects or creativities—where all STEM scholars were required to apply for an internship on or off campus.

ISSN: 2149-8504 (online)

Participants and Context

The participants involved in this study were 34 undergraduate students studying in STEM fields at a university in the northeastern part of the U.S. To recruit student participants, we reached out to students that fit our participation criteria: (a) majoring in a STEM field or discipline, and (b) are part of an ethnical minority federal group. Major STEM disciplines or fields at the institution of interest include biology, biochemistry, molecular biology, civil engineering, structural design and construction engineering, computer science, mathematical sciences, electrical engineering, mechanical engineering. Of these 34 students, about 45% identified themselves as females and 55% self-identified as males. Regarding the issue of race and ethnicity, about 10% identified themselves as Hispanic or Latino; 60% as White American; 18% as Black or African American; 7% as Asian and Pacific American; and 5% as other. After reading, understanding, and signing the informed consent forms, participants were given paper or print versions of the surveys where they completed them in person. The response rate of 100% exceeded the general expectation for collecting survey data because of the small sample size (Miller & Salkind, 2002).

Data Collection and Analysis

Data was collected during one academic year of the NSF Scholars program from the participants at three different stages (pre-year, mid-year, and end-year) using surveys. The component categories of questions or items on the survey comprised of goal orientation, instrumental, and socioemotional abilities. In a broader context and to understand what factors influence customized mentoring of underrepresented students in STEM fields, we created an assessment survey tool to collect data for this research study. Items on the assessment survey tool were selected from the Assessing Women and Men in Engineering [AWE] (AWE, 2008) tool and the Motivated Strategies for Learning Questionnaire [MSLQ] (Pintrich et al., 1991) designed to measure the learning motivating strategies of STEM students.

Sample items on the survey tool include: (a) I feel very much part of the STEM scholars community, (b) I have a regular place set aside for studying, (c) when I participate in STEM professional societies or other extracurricular activities, I feel welcome, (d) my academic program offers me the support and help when I need it, (e) I try to identify students in my classes whom I can ask for help if necessary, (f) this STEM program provides opportunities for me to meet with other faculty and peers, and (g) I enjoy working with other students on group work outside of classes. The mentoring assessments and evaluations were conducted once a new cohort came into the NSF Scholars program.

We evaluated the effectiveness of the NSF Scholars program through an assessment survey tool created from a combination of the AWE and MSLQ items. Statements from the survey tool were on a Likert's scale with a value of 1 as minimum and 6 as maximum. The rating was on a 6-point scale where 1= strongly disagree to 6 = strongly agree. These anonymous surveys were administered to both mentees and mentors before the start of the mentoring program, mid-way through the program, and at the end of the mentoring program. To examine the effectiveness of the mentoring program, data were collected at three different stages: pre-mentoring, mid-year, and end-year. The data collected were examined and analyzed using descriptive statistics and a one-way repeated measures ANOVA. All, analyses were considered statistically significant with $p < .05$, and the SPSS 25.0 statistical software was used for all the analyses.

Results and Discussion

To evaluate the success and effectiveness of the customized mentoring model in the NSF STEM scholar program, we focused primarily on the scholars' survey data and a few testimonials to answer the research questions. As already discussed, the survey data collected were quantitatively analyzed using descriptive statistics and one-way repeated measures ANOVA. The results related to research question 1 (RQ1) is presented first based on the items on the survey that were coded with numerical values to support the quantitative analysis of the data. Finally, the results of research question 2 (RQ2) is also presented and discussed based on the analyses performed on the data in answering the research question.

Research Question 1(RQ1)

RQ1 sought to investigate the descriptive information reveled by the survey data regarding the STEM scholars in this form of customized mentoring. Overall, the mentee participants reported relatively higher scores on most of the survey items from the pre-year data to the end-year data. Examination of the averages from each learning component strategy showed a slight decrease in mentee pre-mentoring and mid-mentoring scores as displayed in Table 1. We assumed that the pre-mentoring mean scores were artificially inflated scores owing to freshman being ambitious about their perceived study strategies for the upcoming college year.

Table 1.
Mentees Responses to Selected Survey Questions

	Pre-Year	Mid-Year	End-Year
1. When I participate in STEM professional societies or other extracurricular activities, I feel welcome.	5.75	5.67	5.81
2. I enjoy working with other students on group work outside of classes.	4.50	5.44	5.38
3. I attend (or intend to attend) faculty office hours at least once a week.	4.67	4.22	4.00

ISSN: 2149-8504 (online)

4. My academic program offers me the support and help when I need it.	6.00	5.44	5.63
5. I have many friends who are studying in my field.	4.25	5.11	5.50
6. Some faculty members know me by name.	5.00	5.25	5.88
7. I have family members or close family friends who are engineers or scientists.	4.75	4.00	4.00
a. Value Component: Intrinsic Goal Orientation Average	5.50	5.11	5.22
b. Value Component: Extrinsic Goal Orientation Average	5.94	5.69	5.58
c. Expectancy Component: Control of Learning Beliefs Averages	5.31	5.08	5.00
d. Resource Management: Help Seeking Averages	4.75	4.58	4.63
e. Resource Management: Peer Learning Average	4.83	4.67	4.92
f. Resource Management: Time and Study Environment Averages	4.90	4.47	4.63

Note: The numbered list are samples items from the survey and the letters list are averages of each learning component

For the mentee assessment scores, we see an increase in almost all categories (with the exception of extrinsic goal orientation) between mid-year and end-year scores. At the end of the program, the mentees average mean scores from Table 1 indicated that mentees in this customized mentoring program were more likely to value their classes without peer influence. The mentees felt that they were able to achieve the grade desired based on their abilities and were more likely to ask for help from peers and faculty, and had improved their time management skills in regard to classwork and studying. This increase in mentees' average mean scores by the end of the year suggests that the customized mentoring model positively impacted the freshman mentees in the NSF Scholar program. Likewise, examination of mentee participants assessment averages as indicated in Table 2, shows an increase in peer learning categories, suggesting that the mentoring model also had a positive impact on the mentees by connecting to peer mentors.

Table 2.
Summary of mean scores on the overall scale and sub-categories

		Treatment Times	
Survey Sub-Categories	Pre-Year	Mid-Year	End-Year
VC: IGO	5.50	5.11	5.22
VC: EGO	5.94	5.69	5.58
EC: CLB	5.31	5.08	5.00
RM: HS	4.75	4.58	4.63
RM:PL	4.83	4.67	4.92
RM: TSE	4.90	4.47	4.63
Overall Scale	**5.21**	**4.93**	**4.99**

Note: VC: IGO = Value Component: Intrinsic Goal Orientation; VC: EGO = Value Component: Extrinsic Goal Orientation; EC: CLB = Expectancy Component: Control of Learning Beliefs; RM: HS = Resource Management: Help Seeking; RM: PL = Resource Management: Peer Learning; RM: TSE = Resource Management: Time and Study Environment.

ISSN: 2149-8504 (online)

Research Question 2 (RQ2)

RQ2 explored the difference in motivation of undergraduate STEM students between the before, during, and after conditions of the programs. Participants' motivation score in STEM was measured at three different points in time (pre-year, mid-year, and end-year) as shown in Table 2 during the program using the data from the motivated strategies for learning survey items. We performed a one-way repeated measures ANOVA to determine whether there was a statistically significant difference of motivation in STEM between the pre, mid, and post conditions. A repeated measures ANOVA was employed here because we wanted to compare the means scores across the participants based on their repeated observation in the program.

All the assumptions of repeated-measures ANOVA were tenable in this data set. Mauchly's test of sphericity indicated that the assumption of sphericity was not violated, $\chi^2(2) = 2.179$, $p = .336$. The results of the one-way repeated measures ANOVA with a Greenhouse-Geisser correction determined that the observed F value was not statistically significant, $F(1.615, 53.310) = 3.280$, $p = .06$, partial $\eta^2 = .09$, which indicated no statistically significant differences of mean motivation scores in STEM attributes over the course of the program. Additionally, the post hoc tests using the Bonferroni correction revealed no statistically significant differences in the training in the STEM attributes from the pre-training to post training of the program. The estimated marginal means for the pre, mid, and post-training data from the one-way repeated measures ANOVA were 5.14, 5.31, and 5.38, respectively. These results showed that the effect of the customized mentoring program was not statistically significant on this group of STEM scholars, which could be due to the sample size. However, the overall mean scores from Table 2 and the one-way repeated measures ANOVA marginal means suggest an increase in mean scores from the pre-training to the post-training of the program. Therefore, we can conclude that the customized mentoring program to an extent had some effect on the students in the area of their instrumental and socioemotional mentoring abilities.

In addition to the quantitative analyses, selected testimonials by the NSF scholars offers additional support to the perspective of the importance of customized mentoring (Morales et al., 2017). For example, one NSF STEM scholar wrote:

"*Being an NSF STEM Scholar is something I am proud of, the club has helped me in many ways my first semester of college. My first semester was pretty rough for me, my biggest problem was adjusting to online work and quizzes, missing a deadline on an online quiz tanked one of my grades this semester but I was lucky to find somebody in the STEM club who has taken the class and helped me with the remainder of the material, and I was able to finish the class with a B+.*"

Another stated

"*While the financial aid I have received for being a STEM scholar is vital to me attending this university, the opportunities that comes with being in this program is invaluable. The STEM club*

ISSN: 2149-8504 (online)

has been very important to my success at this university. I have met several students in this program that I also share classes with. Being involved in this program has only propelled my interest in STEM and computer science." One more wrote "*The STEM scholarship club has provided me with countless opportunities to further enhance my education experience at this university that would be impossible to receive elsewhere. From field trips and guest speakers to fundraisers and volunteering, I could not be more amazed with everything that has been offered to me through the STEM program*."

Limitations and Future Research

There were some limitations associated with this research study. First, it is obvious that we worked with a small sample size. The nature of the small sample size restricted us to the kind of analyses that could be performed quantitatively and generalizability of the results or findings. This could be due to social desirability bias, which is usually associated with survey studies (Tourangeau et al., 2000). We could not generalize the findings to a wider population as the sample included only peer mentors and STEM scholars from a single university in a Northeastern part of the U.S. Moreover, this research study provided less details about the CMM experience; and there was less information regarding the long-term educational experiences and professional career paths for the study participants.

Regarding directions for future research on mentoring STEM underrepresented college students, we recommend examination of this customized model at different university or research sites and with diverse populations. Additionally, it would be of more interest to determine if the CMM can effectively and efficiently incorporate recognized and conventional mentoring programs including undergraduate research assistant positions. According to Thurgood et al., (2010), most STEM scholars get the opportunity to serve as undergraduate research assistants during college years and integrating innovative and authentic models of mentorship such as the CMM has the possibility to offer significant changes and benefits to the educational, professional and career paths of participants. Finally, we recommend an examination of a long-term study associated with the CMM with STEM scholars in summer internships. In the long run, we anticipate it would be noteworthy to understand how participants involvement and participation affected their personal growth, continued education, and professional aspirations in STEM related fields.

Implications and Conclusion

The number of STEM professionals and academics in the United States (U.S.) is now low, and this does not meet the needs of a growing global economy (National Academy of Sciences, 2007). As the supply of qualified and competent STEM professionals continues to shrink, the

ISSN: 2149-8504 (online)

demand for these individuals is on the rise (Wilson et al., 2012). It is important that employers take advantage of this unique opportunity to recruit, train, and retain a STEM workforce before college students graduate through research projects and internships, and the literature supports mentoring as a positive component of these STEM programs (Estrada et al., 2016; Hernandez et al., 2013). There have been some factors that have helped NSF STEM scholars boost their academic achievement in the courses they have taken during this program. The STEM scholars acknowledged and professed that overall, the mentoring program was helpful and beneficial, and the most significant contributing factor to their academic development, performance, and retention in college was the nature and scope of the customized mentoring. Moreover, the mentoring program assisted students in discussing many issues from scholarly to professional and focused on the expectations of each and every student. Overall, from the data analysis, it was clear that most of the STEM scholars perceived and noticed that their personal development and academic success was supported by the customized mentoring model practices.

In summary, despite no statistically significant differences found with the one-way repeated measure ANOVA, our findings suggest a steady increase in the mean scores of mentees learning categories and mentoring characteristics. We believe interpretations and implications can be drawn about effective practices and benefits associated with mentoring underrepresented college students in STEM fields. Our findings suggest that the customized mentoring model and the overall program activities had some positive impact on the mentee participants. Research suggests that mentoring as a pedagogical approach has the ability or efficacy to enhance academic growth and success for students (Kobulnicky & Dale, 2016; Wilson et al., 2012). The NSF-STEM scholars enjoyed the mentoring activities they encountered throughout the customized mentoring model and the present study provided recommendations to researchers and mentors seeking ways to develop and enhance the efforts of their mentees in STEM fields.

The customized NSF-STEM mentoring program has continued to be successful and a tool for recruitment, as enrollment trend for STEM related fields has shown growth for our university. The customized mentoring model had a positive effect and impact on the NSF-STEM scholars in the areas of academic, personal, and social life. As indicated by the STEM scholars' testimonials, the CMM program coupled with other program activities helped the scholars complete their undergraduate studies, continued their education in graduate schools, or even pursued their careers successfully. We believe the scholarships and mentoring support provided to the underrepresented STEM scholars assisted them to succeed in their endeavors and the CMM has the prospect to expand to other settings to provide guidance and growth to underrepresented college students in STEM related fields.

ISSN: 2149-8504 (online)

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ISSN: 2149-8504 (online)

Journal of Research in STEM Education
Vol 7, No 1, July 2021, 21-46
https://doi.org/10.51355/jstem.2021.99

RESEARCH REPORT

Strategically Addressing the Soft Skills Gap Among STEM Undergraduates

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Abstract: *Employers are seeking candidates with uniquely human, or "soft" skills to survive and thrive in their future careers. This article aims to illuminate the soft skills gap of STEM undergraduate students by understanding the soft skills that will be needed in the future of work and the soft skills that students are currently missing. These skills include teamwork, collaboration, leadership, problem-solving, critical thinking, work ethic, persistence, emotional intelligence, organizational skills, creativity, interpersonal communication, and conflict resolution. To address this soft skills gap, this paper also explores various collaboration strategies between employers and academic institutions, such as working jointly on curriculum, raising awareness, establishing leadership support, and building communities of success. These can be implemented to enhance the soft skills capabilities of STEM undergraduate students entering the workforce. This qualitative research examined STEM employers' perceptions of the most essential soft skills needed and missing among recently hired STEM undergraduates. Findings identified the top ten most in-demand soft skills needed for the next five years with leadership and human-connection on the top of the list. Furthermore, the result of this inquiry indicates that the soft skill gap in current STEM undergraduates is not only evident, but it is steadily increasing. To address this problem, this paper suggests that an ongoing synergy is needed between employers and Higher Education Institutions (HEIs) to guide students in developing and acquiring these essential skills. This effort will hopefully improve student employability, increase employer outcomes, and ultimately reduce the nationwide soft skills gap. Also, it provides insights into soft skills that organizations and HEIs should invest in the years ahead.*

Keywords: *STEM education, soft skills, higher education, workforce education*

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To cite this article: Karimi, H. S & Pina, A. A. (2021). Strategically addressing the soft skills gap among STEM undergraduates. *Journal of Research in STEM Education*, *7*(1), 21-46. https://doi.org/10.51355/jstem.2021.99

ISSN: 2149-8504 (online)

Introduction

Since the 1990s, research studies have continuously proven the importance of soft skills for both the workforce and organizational success (Bernd, 2008; Deming, 2017a; Livia et al., 2017; Mitchell, 2008; Nguyen, 1998; Patacsil & Tablatin, 2017; Rao, 2016; Williams, 2015; White & Shakibnia, 2019). World Economic Forum Founder and Executive Chairman Klaus Schwab asserts that emerging technologies are changing everything--how we relate to one another, the way we work, how our economies and governments function, and even what it means to be human (Schwab & Davis, 2018). Further research compliments this view by indicating that programs which enhance soft skill competencies have an important place in our society (Heckman & Kautz, 2012; Heckman & Mosso, 2014). In fact, soft skills are becoming a decisive factor towards graduate employability in the 21st Century economy (Society for Human Resource Management, 2019; U.S. Chamber of Commerce Foundation, 2018; Wilkie, 2019a).

Soft skills and success

James Heckman, a Nobel Prize-winning economist, determined that having soft skills literacy statistically leads to success in life—more so than technical skills literacy. He cites evidence that demonstrates that soft skills competencies are essential for achieving professional and personal life success. Heckman's timeless recommendation to educators--published more than two decades ago--is to consider investing in a sustainable soft skills educational system that trains students in the art of interpersonal, professional, and leadership/management skills in order to help develop a successful pathway for future students (Heckman, 2000).

Balcar (2016) demonstrated a significant correlation between soft skills and wage determination, with individuals possessing soft skills competency tending to have higher salaries than their counterparts. Moreover, research by Deming (2017a; 2017b), found that the combination of soft and technical skills has a positive impact on job promotion and wage increases, enabling improved individual performance and better organizational outcomes.

Defining soft skills

Since the 1990s, the need for soft skills competencies in the workforce has been the subject of many studies (e.g. Bernd, 2008; Deming, 2017a; Heckman & Kautz, 2012; Livia et al., 2017; Mitchell, 2008; Nguyen, 1998; Williams, 2015). Throughout these studies, the concept of soft skills has been defined in distinct ways. Academic discourse on soft skills generally refers to abilities like teamwork, collaboration, leadership, problem-solving, critical thinking, work ethic, persistence, emotional intelligence, organizational skills, creativity, interpersonal communication, and conflict resolution.

ISSN: 2149-8504 (online)

According to Colburn (2018), there are two broad categories of soft skills: interpersonal (i.e. skills between the self and others) and intrapersonal (i.e. skills within oneself). Interpersonal soft skills refer to one's core skills that propel the individual's ability to perform and fit into a specific job. These skills include listening, asking questions, working in teams, resolving conflicts, and showing empathy. Intrapersonal skills include self-awareness, proactiveness, goal setting, time management, perseverance, and self-management (Colburn, 2018). According to a recent survey of over 1000 business leaders conducted by the Society for Human Resource Management (2019), there is a lack of soft skills in both categories, specifically in areas of professionalism, business acumen, critical thinking, and lifelong learning.

Pritchard (2013) believes that soft skills should be defined differently, depending on the industry sector in question. For example, the soft skills needed in the manufacturing sector have been identified as problem-solving, reliability, verbal communication, listening, and teamwork. In the healthcare sector, they include communication with clients, written communication, positive attitude, and customer service skills. In office-based settings, skills that are most sought after by employers are verbal communication, written communication, teamwork, professionalism/integrity, and organizational skills (Pritchard, 2013).

The need for soft skills in the future of STEM work

The labor market is projected to undergo significant technological and scientific breakthroughs, which are rapidly shifting the future of the work tasks performed by humans and those performed by machines and algorithms (World Economic Forum, 2018). With the rise of emerging technologies, such as artificial intelligence, machine learning, and automation entering our workforce, the future of employment will necessitate soft skills that machines cannot replace (Wilkie, 2019a).

Due to the increasingly competitive global economy, national surveys of businesses and nonprofit leaders indicate that employers are concerned about whether the U.S. is producing enough college graduates with the skills and expertise to contribute to the changing workplace (Association of American Colleges and Universities, 2018). They wonder whether new hires can help companies and organizations grow and succeed. This is because one of the greatest threats facing organizations today is the STEM talent shortage, and many organizations do not appear to be actively or effectively tackling the issue (LaPrade et al., 2019). For an organization to continue to grow and prosper, it must be understood which skills its future employees must master (Cimatti, 2016). Individuals with soft skills will be in greater demand than those without these abilities--regardless of their technical skills and experiences (American Association of Colleges and Universities, 2018; LinkedIn, 2019).

In fact, as industry reports indicate, employers are placing higher importance on soft skill competencies than they are on technical skills (LinkedIn, 2019; Society for Human Resource

Management, 2019). However, research also claims that soft skills competencies in prospective employees have become a challenge for employers to find, thus impacting their organizational efficacy (Crawford et al., 2011; Sarkar et al., 2016; U.S. Chamber of Commerce Foundation, 2018; White and Shakibnia, 2019). Employers realize that they cannot solve the skills gap issue alone and that more work needs to be done by businesses and educational systems to ensure that the U.S. workforce is prepared for the future of work (Society for Human Resource Management, 2019).

It is essential to assess, enable, and strengthen the STEM workforce to ensure continued U.S. competitiveness and prosperity (Association of American Colleges and Universities). Soft skills are transferable skills across all disciplines. The lack of competency has implications for all stakeholders: students, employers, and educators (Association of American Colleges and Universities, 2018; White & Shakibnia, 2019).

Soft skills gap

Research from the past two decades indicates that employers are seeking and struggling to find well-rounded college graduates that are competent in both hard and soft skills (Cimatti, 2016; Crawford et al., 201; Patascil & Tablatin, 2017; Prichard, 2013; Rao, 2016; Sarkar et al., 2016; White & Shakibnia, 2019; Williams, 2015). A recent survey by the Association of American Colleges and Universities (2018) assessed the opinions of 1000 business executives and hiring managers from diverse organizations in private, public, and non-profit businesses. The survey reported that employers perceive a notable gap between crucial learning outcomes (mostly soft skills literacy) and the preparedness of recent college graduates. These results, listed in Table 1 below, indicate that there is a significant soft skills gap between essential learning outcomes that employers tend to prioritize and the low levels of preparedness that they tend to observe in recent graduates.

Table 1.
College Graduate Preparedness (Association of American Colleges and Universities, 2018)

Key Learning Outcomes (Soft Skills)	**Recent college grad preparedness (%)**	**Considered highly important (%)**	**Preparedness Gap**
Critical thinking	34	78	-44
Appy of knowledge to real-world	33	76	-43
Effective written communication	33	76	-43
Self-motivation	35	76	-41
Effective oral communication	40	80	-49
Ability to work independently	38	77	-39
Ability to work effectively in teams	42	77	-35

ISSN: 2149-8504 (online)

The soft skills discrepancy between expectations and reality is affecting graduate employability (Lewis, 2018; Matsouka & Mihail, 2016; Sarkar et al., 2016). A survey of over 1,000 college students indicates that only four in ten U.S. college students feel well-prepared for their future careers (McGraw-Hill Education, 2018). In another study, more than 65 percent of undergraduate students felt very confident about their soft skills competencies, while only 30 percent of employers felt the same (Lewis, 2018). Furthermore, 70 percent of recent college graduates reported a high level of confidence in their critical thinking skills, while just 26 percent of employers conveyed the same confidence in their abilities. Looking at collaboration skills, nearly 80 percent of recent college graduates had a strong perception of their abilities to work successfully in a team. In contrast, less than 40 percent of employers reported the same sentiment (Lewis, 2018). These inconsistencies between students and employers illustrate the complexities of the soft skills gap.

Disconnect between academe and employers

Meanwhile, chief academic officers and other educational leaders argue that they are providing competent, skilled graduates into the job market (Bidwell, 2014). According to the National Academies of Sciences, Engineering, and Medicine (2016a; 2016b), 96 percent of today's educators believe they are providing students with a STEM education that delivers workforce-ready graduates to the job market. However, only 11 percent of U.S. employers agree with these assertions.

Prior research points to a national misalignment in the workforce and connects it to the outcomes of higher education in its mission to prepare college graduates for the workplace (Association Of American Colleges and Universities, 2018; J. P. Morgan, 2019; White & Shakibnia, 2019). This misalignment has been attributed to a widening imbalance that prioritizes technical skills over soft skills (Patacsil & Tablatin, 2017). As a result, according to the U.S. Chamber of Commerce Foundation (2018), somewhere along the path from education to employment, the system is not routinely equipping students with the soft skills they need to succeed. This imbalance is present despite the value that employers across all sectors place on soft skills (Association of American Colleges and Universities, 2018; LinkedIn, 2019).

Most engineering and technology university programs have a thorough curriculum that prepares students with courses that traverse the spectrum of technical disciplines (Darabi et al., 2017). Accreditation bodies like the Accreditation Board of Engineering and Technology (ABET) require students studying in the technology and engineering fields to receive training in soft skills such as lifelong learning, communication, and multidisciplinary teamwork (Accreditation Board for Engineering and Technology, 2017). However, studies continue to find that graduates are insufficiently familiar with these soft skills upon the transition to the professional work environment (Darabi et al., 2017; Livia et al., 2017; White & Shakibnia, 2019).

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A study by West (2012) concludes that universities prepare STEM students for a range of professional roles throughout their curricula offerings and teaching approaches, including collaborative practices with employers and other schools. White and Shakibnia (2019) view universities as a key part of the STEM ecosystem and state that universities are not aligned with the needs and demands of the other key partner in the STEM ecosystem: the employers. This misalignment of outcomes between educators and employers is catapulting deficient STEM college graduates into a job market that particularly depends on soft skills.

The magnitude of the soft skills gap is significant, and if student training is not managed correctly, the risk of a widening skills gap pervades (World Economic Forum, 2018). STEM industries across the globe play a central part in maintaining market competition and improvement. When the interests of academia and business are not united, companies struggle to find competent employees, thus impacting their organizational effectiveness within competitive markets. The time to develop the landscape of the future STEM workplace is now (U.S. Chamber of Commerce Foundation, 2018; World Economic Forum, 2018; White & Shakibnia, 2019).

Purpose of the study

The soft skills gap presents an opportunity to explore strategic approaches that offer a high impact pathway focused on closing the skills gap (LaPrade et al., 2019; Sarin, 2019; White & Shakibnia, 2019). The skills gap is not dissipating and appears to be increasing in severity (LaPrade et al., 2019; Society for Human Resource Management, 2019). It is essential to equip students with soft skills that are relevant and valued by employers to create economic success, increase productivity, and continue the path of innovation in the modern global economy. Building and thriving in a vibrant STEM ecosystem can help organizations to participate profitably in the global market (Penprase, 2018).

This qualitative research used semi-structured face-to-face interviews. This methodology has been chosen due to its ability to enhance the depth of conversation and to increase understanding of the causes, effects and possible solutions to the current soft skills gap (Charmaz, 2003; Creswell and Poth, 2018).

Method

Subjects

The participants of this qualitative study were local hiring managers, healthcare executives, and healthcare professionals throughout the state of Kentucky, whose organizations have recently either hired or worked closely with entry-level STEM graduates. The industry of focus is healthcare, since it is the fastest-growing job sector within the local market (Kentucky

ISSN: 2149-8504 (online)

Center for Statistics, Education and Workforce Development Cabinet, 2018). Ideal participants for grounded theory research, as Munhall (2012) suggests, are individuals who have experienced the phenomena in question and are willing to articulate their experiences to share relevant information that is reflective and informative.

Purposive sampling was used to focus upon participants who met the following criteria: 1) fulltime employees of STEM-focused healthcare organizations in Kentucky; 2) a minimum of least three years of experience within their respective organizations; 3) have recently hired or worked closely with STEM college graduates. In addition, participants were recruited using snowball or chain sampling, which is used to identify people of interest by leveraging social networks and mutual connections (Creswell & Poth, 2018). There were 27 participants in this study coming from a diverse background, from small entrepreneurs to Fortune 500 organizations. Four of the participants were CEOs, four were Vice Presidents, five were HR managers, six were directors, and eight were managers in their departments. The size of the represented firms also varied. Four participants worked at a small firm, twelve at a medium sized firm, and eleven at a large firm. Twelve of the participants were women, and fifteen were men.

Data collection

Data were gathered through semi-structured interviews to give participants an ample opportunity to reflect on the interview questions and describe their insights and understandings of the soft skills gap phenomena. The structured interview questions focused on analyzing the central phenomena to detail the emerging theory. To ensure that all information was captured during the data collection, a high quality professional Evistr digital voice recorder was used to capture the data from semi-structured interview questions. This qualitative research followed Walker's (2012) guidelines, which suggest that data saturation occurs when continued data collection yields no new insights, but is primarily confirming the findings from previous data, and the abstraction of formal theory emerges from said findings (Glaser & Strauss, 1967).

Data Anlaysis

The data analysis procedures characterized by open, axial, and selective coding – as recommended by Strauss and Corbin (1998) – began soon after the transcriptions from each interview were completed. Using this approach, the researcher sorted, coded, and analyzed the data as it was collected. Themes and patterns were uncovered during the data interpretation phase to make meaning of the raw data. In this phase, the participants' feedback was reduced and broken into themes, clusters, categories, and subcategories based on their characteristics, properties, and dimensions (Wilkin, 2010). Finally, the conclusive results were coded in themes according to the framework of grounded theory (Strauss & Corbin, 1998).

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Microanalyses were also conducted to mine for pieces of information that were kept open for possible consideration, to avoid jumping to conclusions. With each participant, the researcher searched for special codes that may have provided valuable insight into the perspectives of the overall participants (Charmaz, 2003; Strauss & Corbin, 1998; Wilkin, 2010). This process was chosen because it enables the illumination of more nuanced insights regarding the soft skills gap.

Coding paradigm

The study was guided by the coding paradigms model established by Strauss and Corbin (2015), which divides the data into emerging categories and subcategories using the following six variables: context, casual conditions, intervening conditions, occurring conditions, action/interactions, and the phenomena. The data within each category and subcategory was consistently assessed for its fitness within each of the six variables mentioned earlier. This data analysis was repeated for each participant until data saturation occurred or the researcher was no longer able to add more content to the existing data set.

Open coding

The coding analysis for each interview began with a process called open coding. It entails breaking down the raw data into discrete parts, then carefully examining each section, line by line, for similarities and differences (Strauss & Corbin, 1998). In grounded theory research, open coding is the analytical process by which concepts are generated using observed data and phenomena. This occurs with the help of labeling concepts, which define and develop categories based on their properties and dimensions. This process then leads to the application of key terms and phrases that are written in the margins of the transcripts to identify concepts and categories (Wilkin, 2010). Key terms are grouped into subcategories based on their characteristics, properties, and dimensions, leading to the emergence of categories that create the foundation for the development of the grounded theory in explaining the phenomena (Corbin & Strauss, 2008; Eaves, 2001).

Axial coding

Axial coding was also used to develop the study's theoretical model. Codes were sorted into groups by refining the concepts. This coding process linked the developed categories identified in the open coding phase with subcategories, by taking their properties and dimensions into consideration. The axial coding process enables the researcher to identify the relationships among the actions, interactions, and consequences associated with each participant's experiences (Böhm, 2004).

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Selective coding

Once the axial codes were identified, the next step in the data analysis was to refine the generated codes and categories, to facilitate the development of the grounded theory. This process, called selective coding, includes the following sequential steps: identifying the central category, relating the categories to subcategories, validating those relationships, writing the storyline to connect categories, and finally, refining the data so the grounded theory can help explain the phenomena (Eaves, 2001; Strauss & Corbin, 1998).

Results and Discussion

The following three major themes emerged from the data describing how employers view the soft skills, the soft skills gap, and how they are working to address the soft skills gap within the STEM workforce:

- Theme 1: Soft skills gaps exists among recent STEM undergraduate new hires
- Theme 2: Specific soft skills will be in demand for the future
- Theme 3: Employers and academic institutions are not systematically collaborating to help design undergraduate curricula that foster soft skills competencies

Theme 1: Soft skills gaps exist among recent STEM undergraduate new hires

When employers were asked if they had ever experienced a soft skills deficiency amongst their new STEM undergraduate hires, 100 percent of the 27 interviewed employers said yes. These responses align with prior research, which claims that the misalignment of interests at the intersection of the workforce and higher education is generating a national skills gap across industries, particularly in the area of soft skills (National Chamber of Commerce, 2018; Patacsil & Tablatin, 2017). The most reported soft skills that are lacking amongst recent entry-level STEM hires in the healthcare industry are: forming a 'human connection' with patients or colleagues; critical thinking; creativity; receiving/giving constructive feedback; professionalism; communication and collaboration. The following comments by employers are representative:

> "I see the soft skills gap every day in areas of collaboration, communication, and teamwork mentality. It's very endemic."
>
> "We are constantly working on managing productivity and identifying gaps in productivity. The ability to communicate concisely and effectively is a huge gap—the ability to be self-aware during communication and self-edit, which goes into that same thing. And for the same reason, communication in writing is similarly challenging for those same people."
>
> "Creative thinking shallowness, which is just thinking they can solve a problem right away without going back and researching what's been done before. Have we had this

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issue -- had we had communications with this customer before, but just realizing that the world didn't start right in that instant? They have to have more of a well-rounded concept of history and how things run."

"It doesn't matter what qualifications they have; if they do not have the soft skills to implement their technical skills, they are absolutely no good."

Theme 2: Specific soft skills will be in demand for the future

The increasing demand for soft skills renders it essential to understand which soft skills will be most necessary in the healthcare industry. In an attempt to uncover this need, the interviewed STEM employers were asked to express their views on the soft skills that they think future STEM undergraduates will need before entering the healthcare industry, specifically in the period of 2020 to 2025. The top soft skills that employers identified as necessary to have in the future, within the STEM healthcare industry, are shown in Table 2.

Table 2.
Soft skills STEM employers identified as necessary in 2020-2025

Necessary soft skills	**Employers who mentioned this soft skill**
Leadership	93%
Human Connection	89%
Communication	81%
Creativity	70%
Collaboration	70%
Critical Thinking	63%
Empathy	56%
Problem Solving	44%
Emotional Intelligence	37%

Leadership

Employer perceptions ultimately indicate that a change in thinking is necessary to modernize how we think about the future and our subsequent relationship with soft skills education. Specifically, employers noted the emerging changes regarding person-to-person interaction, as well as our personal relationships with data and technology more generally, effective leadership, the evolution of individual work patterns in the face of immense technological advancement, and finally, the skills that will be required to ignite growth throughout the healthcare industry. In fact, the results from semi-constructive interviews demonstrate that 93 percent of all interviewed employers rank the soft skills related to leadership as the single most essential skills to master in the future of healthcare and STEM.

One employer indicated entry-level employees that grew in their organizations are those with these soft skills “coming in every day, showing leadership capabilities. When their team faces a challenge, they're rolling their sleeves up, and they're going with that challenge. They are smiling. They are professional. They are taking that personal initiative to stand out.” Another HR employer said, “If I have two candidates and both are bringing the same technical skills to the table, but one is energetic, adaptable, good in a team environment, is a leader, and passionate about what they do, that's going to carry that candidate further down the road.” This finding demonstrates that the path to a more inclusive and human-driven future begins with the soft skills of leadership. This means it will become increasingly essential for future graduates to master an array of leadership skills, including the abilities to build relationships and collaborate with others.

The good news is that leadership skills can be taught, just like any other soft skill. Social sciences courses in humanities, philosophy, psychology, and civics, for example, can help improve these skills, and yet STEM academics have failed to recognize their importance in undergraduate curricula and course requirements. For example, a significant skill that is typically lacking in new engineering graduates is the ability to lead a team, or even work effectively as a member of a team, the latter of which is frequently identified as critical to the success of an engineer (Brown & Ahmadian, 2014). Project management is another skill that is often neglected in engineering or science curricula, even though it is important for engineers who end up managing teams, projects, or departments.

In the face of these conditions, employers have indicated four major categories of leadership--self-leadership, peer leadership, team leadership, and organizational leadership--that they believe are essential for future undergraduates to attain. They suggest that courses begin with human interaction-based strategies for mastering self-leadership and peer leadership, gradually transitioning to material regarding team leadership, and then finally organizational leadership. Employers emphasized that leadership skills are even expected from entry-level employees who need these skills to eventually transition into upper management and beyond.

For instance, one interviewee mentioned how self-leadership among graduates is necessary for creating a productive teamwork environment. He noted, “People just need to understand why they’re a member of the team. They're expected to be a leader of everything that they do in their team. And that's a necessary factor for them to understand that. That's kind of a hard lesson to learn.” Likewise, another employer mentioned the significance of developing self-leadership amongst recent graduates, “…so that they can take future leadership positions as they become available.”

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One interviewee signified the importance of leadership and the ability to make business decisions with empathy in mind for their business to thrive and succeed: "Individuals with soft skills and capabilities of technical and leadership skills, all of that plays into the nuances of decision making. How we make decisions, and the impacts of our choices will have on the growth of the business. And so in my opinion, those folks that have the soft skills oftentimes are able to make decisions with empathy that think about the human element whenever we make decisions and the impact that they can have on both our employees but also our customers. Often, those decisions have the customer in mind --at the center of our decision-making. That is what is driving the distinction between successful businesses and businesses that are struggling."

Human connection

The future of the STEM healthcare industry necessitates that graduates have the ability and skills to interact with their clients, patients, or colleagues, to form human connections. This goal is also reflected in the World Economic Forum's *Jobs of Tomorrow* report (2020), which asserts that humanity and the ability to connect with people amid the rapid development of new technologies are at the core of what tomorrow's workplace will require. In fact, 89 percent of interviewed employers indicated that human connection would be essential to produce insights for better patient care, creative solutions/outcomes, and strategic differentiation, which supports revenue growth, personal growth, and organizational survival.

Employers also emphasized that future STEM graduates will need soft skills competencies to help facilitate personal interactions with their colleagues, clients, or patients. Many of these individuals placed gret value in the power of human interactions, which essentially serve as the differentiator between humans and emerging technologies, such as artificial intelligence and robotics. Although still at a nascent stage of this spectrum of technological development, employers are already seeking candidates with uniquely "human" soft skills, like conflict resolution, problem solving, the generation of new ideas, collaboration, and critical thinking (Barr, 2019). These skill competencies are a necessary component of the effective delivery of tasks related to technical skills.

Throughout most interviews, employers expressed that future graduates should fundamentally understand what it means to be human. According to employers, when this sense of humanity becomes intertwined with one's technical capabilities, one can become better equipped to achieve desired results. Employers listed the soft skills below that demonstrate the power of human connection in STEM, and notably, how noted soft skills related to human connection can help employees improve at their job:

- Ability to connect with clients and patients
- Knowledge of what it truly means to be a human

- Facilitating interaction with the patient
- Ability to build a relationship and form connections
- Ability to build rapport with someone
- The importance of self-care and being nice to oneself
- Staying connected with the humanity in oneself and surrounding individuals
- Investing in the other humans around oneself
- Understanding what it means to be a human

Communication, collaboration, creativity, critical thinking

Based on participant responses, the major in-demand skills of tomorrow are the Four C's: Communication, Collaboration, Creativity, and Critical thinking. One employer stressed, "the ability to communicate ideas and be a force multiplier" is what empowers employees with the skills that engender innovation and unique service offerings. Another employer indicated that "communication is at the crux of everything." According to these qualitative interviews, the future of the healthcare workforce needs individuals who possess effective communication in all formats--face-to-face, virtual, verbal, non-verbal, email, oral, and written.

Furthermore, 19 out of 27 employers interviewed reported creativity and collaboration as essential skills for their organizations. Future graduates need to foster competencies that enable them to think outside of the box and collaborate to generate innovative ideas. For this to happen, 17 employers believe future graduates need to learn how to use critical thinking capabilities. This skill is imperative for assessing or facing an issue and effectively solving it. Employers need graduates who have self-realized analytical thinking capabilities. Additionally, all four C's are needed to solve problems and generate optimal solutions. By learning these soft skills competencies before graduation, students experience better opportunities in the workplace, therefore enhancing both their personal and organizational growth.

Empathy

Empathy can help professionals solve problems by enabling them, "to understand the emotions that a person is going through," as stated by one participant. In doing so, this mindset can lead to solutions such as enhanced patient care in a hospital setting or a more seamless user experience while navigating a new product or software application. STEM employers want to see future graduates integrate human qualities like empathy and compassion in their jobs as a tool for achieving desired outcomes within organizations.

According to 56 percent of employers interviewed in this study, when future nurses, therapists, engineers, technologists, and dental hygienists deliver services to their customers and colleagues, they need be able to draw upon their empathetic competencies--alongside their technical skills--in order to build trust, respect, and support with their customers and colleagues. Throughout interviews, employers from doctor's offices or hospital settings discussed the need

ISSN: 2149-8504 (online)

to show empathy--instead of sympathy--towards their patients. Being able to sit down and successfully empathize with patients and their families will be crucial to the success of both students and businesses.

Another application of empathy that employers disclosed is found in a specific use case. Technology employers expressed the essentiality of teaching future computer scientists or software developers how to be mindful of who will use their services, therefore incorporating empathy in their product designs. For instance, software built for an elderly population might need extra features to make it more user friendly. In designing such an interface, future technologists will need leverage their empathy throughout the development process by foreseeing the outcome of their work and how it is related to the human experience. This means developers will need to empathetically incorporate their technical user experience knowledge and think about how their technological creation may help or hinder the user's ability to solve their problems while using the product.

Problem-solving

In addition to the previously mentioned soft skills, 44 percent of employers in this study prioritize skills related to problem solving, such as the ability to resolve issues creatively. One employer said, "Creative problem solving is one differentiator," while another stated that, "Problem solving skills are going to be super key in the future." Specifically, employers want entry-level graduates to have the ability to solve problems before asking a leader within their organization for assistance. However, employers also want graduates to feel comfortable asking questions if they encounter issues while tackling these endeavors independently.

Moreover, employers prefer for their employees to offer problems and solutions simultaneously. As one employer said, "Don't tell me what is wrong, tell me how to fix it." This skill can be developed in an academic format by teaching students how to leverage multiple types of available resources instead of solely relying on Google. A noted example of a helpful yet untapped resource that can improve said problem solving efforts is the wisdom of colleagues who have experienced similar problems in the past.

Emotional intelligence

Emotional Intelligence (EI) was mentioned by 37 percent of participants as a soft skill that would be needed between 2020 and 2025. One employer described EI as "one's ability to trust their gut" and another describes it as the ability to, "read expression and body language." Being in the healthcare industry, employers also explained that future STEM graduates need to be emotionally intelligent and "not so focused on technology and use their common sense." In fact, one respondent said, "common sense is the superpower."

Research in this space generally concludes that emerging technologies, which include big data, automation, and data digitalization, are transforming the healthcare industry (Barr, 2019; Penprase, 2018). As such, soft skills can play a significant role in connecting these technologies with humans (Barr, 2019). According to the results of this study, soft skills are--and always will be--essential tools for the organizations of both today and tomorrow.

Theme 3: Employers and academic institutions are not systematically collaborating

This study aimed to understand how employers are working with academia to foster soft skills development. The two avenues that were of specific interest were collaboration between academia and industry and the extent that partnerships were effective. As a result of this inquiry, a third theme emerged: systematic, collaborative synergies simply do not exist in the relationships between many employers and local educational leaders. Employers claim that the connection between the two entities is so detached it is blocking the opinions of employers from the design and development of STEM undergraduate curricula.

This lack of dialogue and engagement was evident amongst the employers who participated in this study, 78 percent of whom do not partner with local academia to enhance STEM students' soft skills competencies. A key method of improving this cross-pollination is through the industry advisory boards of universities. According to the interview data, 81 percent of employers do not sit on any such advisory boards, meaning their expertise is not being shared in the academic arena.

Strategic actions to reduce the soft skills gap

Jointly work on curriculum

A strategy one employer suggested was for industry and academia to join forces and craft student curricula together to ensure its relevance for current and future workforce needs. Another suggested approach was to integrate soft skills education into technical STEM courses at all levels. This comprehensive approach would hopefully entrench this way of thinking into the first year of undergraduate education up until graduation. Soft skills development needs to be taught alongside technical skills. When the two skillsets effectively intertwine, students are better equipped to understand the practical relevancy of these skills.

It is essential for soft skills education to be woven through an entire STEM program and not relegated to just one course. There should be a section in each disciplinary curriculum that specifically lists soft skills as a set of learning objectives for each course. Soft skills development takes time to develop, and students need to practice these skills through the diverse perspectives that differing courses can provide. Rather than relying on these skills to magically develop in the workplace post-graduation, STEM courses should have these skills repeatedly targeted to enable

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students to learn: 1) how to communicate effectively; 2) articulate themselves; 3) become a dependable team member; 4) demonstrate compassion towards their colleagues; 5) use empathy when creating a technical product; 6) offer constructive feedback; 7) accomplish a task individually or within a team; 8) use creative thinking to solve problems; 9) demonstrate confidence and assertiveness; and 10) how to attain or maintain a job.

According to Heckman (2019), the encouraging element of soft skills development is that soft skills can be mastered by all students, regardless of their technical disciplines or personal attributes. However, this is only possible when educators invest in a sustainable, systematic approach to teaching that is specifically catered towards soft skills education. There is even a proven return on investment concerning soft skills training and proficiency (Deming, 2017a, 2017b; Heckman, 2019). Given these research outcomes, we may find that targeting soft skills competencies might be beneficial for individuals and organizations to not only survive--but *thrive*--within the 21st Century STEM workforce.

Raising awareness

A common solution for addressing the soft skills gap that employers often suggested throughout interviews was to raise awareness of the gap and why there is such a subsequently high demand for soft skills. Employers continuously reiterated that reducing the soft skills gap is a community effort, and it begins with awareness. To ensure awareness of the importance of soft skill competencies in the local healthcare market, local employers and educators should strategically market these skills as a pathway to economic prosperity (Livia et al., 2017; Sarkar et al., 2016; West, 2012). This solution is an avenue for both college graduates and job seekers to develop the skills to be prepared for the local STEM job market. However, STEM undergraduate students in Kentucky are rarely informed about the potential that a soft skills education can provide, as one interviewed employer noted: “One of the things that we are working on, first and foremost, is to build self-awareness. So, if the students aren't aware of the areas in which there are opportunities for growth, then there is no way that they can hone in on the skills that they need.”

To address this knowledge gap, STEM employers should develop aggressive outreach strategies to increase the awareness of critical soft skills needed to build a steady talent pipeline. To do so effectively, they should first work jointly with academia to determine what soft skills are needed and then partner with academic institutions to develop strategic counseling and tools that STEM undergraduate students can use to develop their career pathway to meet the needs of the local job market.

Raising awareness can simultaneously illuminate the content that should be integrated into STEM courses and offer students the opportunity to enhance their learning competencies. This idea is supported by prior research which concludes that the integration of technical and soft skills is useful for enhancing the efficacy of student learning (Manullang & Kons, 2010; Woodward et al., 2010). Most of the employers in this study also think that educators need to be made more aware of the soft skills gap too. Without an established relationship between academic institutions and private organizations, this study demonstrates that oftentimes the foundation for this strategy is lacking. It is precisely this lack of connectivity that is impeding the flow of employer needs from being communicated to educators and students.

However, conversations with the small number of employers that were in tune with the academic environment suggested that the collaborative process can start with open communication and relationship building. Both employers and academic institutions can initiate this connection and should equally assume the responsibility to do so.

Establish leadership support

Leadership is defined as "the sets of activities required to articulate an organization's vision and ensure that all its stakeholders will support the vision" (Stid & Brandach, 2009, p. 36). Similarly, Northouse's (2007) definition of leadership "is a process whereby an individual influence a group of individuals to achieve a common goal" (p. 3). In lieu of the lack of strategic direction from academic leadership to facilitate a soft skills education, employers in this study expressed the need to establish leadership support, with the goal of collaborating with internal and external stakeholders. This relationship building, starting from the top of the hierarchy, is essential for initiating any engagement program.

In fact, the results of this study show that employers believe leadership is key for building engagement, collaboration, and long-term partnerships. This is exemplified by employers whose organizations did have the leadership support they needed to pursue a collaborative approach with academia, which subsequently allowed them to cultivate better experiences with their new hires.

However, the success of these outcomes depends on the strength of leadership support on both sides: in academia and in industry. For instance, local STEM employers who observed keen interest from academic leaders to collaborate, consequently felt enticed and inspired to get engaged with local students. An equal level of enthusiasm from leaders in academia and industry is required in to develop the partnership and achieve both parties' goals and objectives. Collaboration that begins at the highest leadership levels, with a student-centric vision at its core, ultimately benefits the community at large.

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Active collaboration with academia

There are many traditional ways to collaborate with academia that include internships, co-ops, and externships. However, one employer noted that we need to update these approaches using a more contemporary perspective that targets the needs of students. He noted, "I think that even more can be done [to address the soft skills gap] because this is a give and take. This isn't just the corporations needing a new workforce… students need jobs. So, trying to figure out how to connect these dots is really important for the workforce development of our community."

Another employer emphasized that active collaboration is important for staying informed about the evolving needs and demands of the other party. This perspective is aligned with prior research, which asserts that somewhere along the road between education and employment, the system is not providing students with the skill competencies they need to succeed in the workplace (U.S. Chamber of Commerce Foundation, 2018; White & Shakibnia, 2019). Mutual awareness about each party's needs can enable appropriate accommodation and an ultimate alignment of interests.

Build a community of workforce success

Employers realize that they need to collaborate with academia to simultaneously tackle the soft skills gap and enhance the strength of the community's workforce. One participant said: "This a community effort that must be made a priority." Some employers interviewed were able to do this successfully for several years, enhancing their organizational goals and local communities. As one employer remarked, "We come together, and we talk about what kind of skills we need as people come out of college so that universities can respond to that and build programs that will meet the needs of employers, two, four, eight years in the future."

The labor force has a significant impact on regional economic vitality, and organizations cannot innovate and grow their businesses without skilled workers (LaPrade et al., 2019). If organizations cannot find a talented workforce in their local areas, they migrate to other regions, searching for workers with skills needed to remain competitive. As a result, a decline in the skilled workforce can profoundly impact a region's economic competitiveness and value proposition (LaPrade et al., 2019).

Investing in future graduates' education before they enter the workforce has benefited employers that chose to invest their time and resources in fostering and developing the soft skills competencies of students before they had joined their organizations. Prior research echoes this phenomenon. It indicates that soft skills training has a direct impact on the return organizations and individuals realize from their investments (Balcar, 2016; Deming, 2017; Heckman, 2000). In fact, Heckman's recommendation to educators is to consider investing in a sustainable soft skills educational system that trains students in the art of interpersonal, professional, and leadership/management skills to help develop a successful pathway for future students. This perspective helps explain why the top skills that interviewed employers tend to value are leadership and human connection.

The employers who participated in this study continuously felt that the only way to secure their competitive advantage was by working strategically with academia to align STEM coursework with the needs of local businesses. In fact, throughout most interviews, employers indicated that it is essential to look at the soft skill gap phenomenon as a community effort, rather than a university-only responsibility. However, many respondents did say that they want educators to initiate this process to demonstrate their commitment to the collaborative relationship--namely regarding academia's willingness to adapt to the suggestions made by employers.

Conclusion

STEM Education

The future of competition in a globalized America is dependent on a strong workforce rooted in science, technology, engineering, and mathematics (National Academies of Sciences, Engineering, and Medicine, 2016). The STEM discipline has played a significant role in the nation's trajectory towards innovation and economic growth, and we will continue to rely on STEM experts to support this trajectory (White & Shakibnia, 2019). However, based on an extensive report, industry and employment experts are concerned that our nation may not have an adequate supply of skilled technical workers to maintain its global competitiveness (Olson & Riordan, 2012). As the global economy grows, ten of the fourteen fastest-growing industries will require a STEM education (Olson & Riordan, 2012). For these reasons, it is essential to proactively prepare workers and students for the occupational needs our society will demand from the STEM fields. A future driven by exponentially increasing technological change requires us to take these employment gaps seriously (Cimatti, 2016; Cinque, 2015; White & Shakibnia, 2019).

STEM education needs to be strategically aligned with the industry needs (Bloomberg, 2018). According to Sarkar et al. (2016), employers are recommending that changes to the pedagogy are needed. One of the significant changes they suggest in regard to teaching tactics is centered around the differences between open-ended and formulaic problem-solving. By incorporating more inquiry-oriented learning, students learn problem-solving skills that can range across a broad spectrum of situations. Additionally, this environment more closely resembles the realities of problem-solving in a professional space. For this reason, integrating an inquiry-oriented teaching approach might provide students with increased opportunities to develop soft skills competencies such as critical thinking, teamwork, self-directed group learning, and communication skills (Rayner et al., 2013).

ISSN: 2149-8504 (online)

The calls for systematic and transformational improvements throughout undergraduate STEM education have been numerous and reiterated over the past 25 years (McKenna et al., 2014). According to Khatri et al. (2017), the undergraduate STEM education community has developed a large number of innovative teaching strategies to improve student learning outcomes. The empirical study conducted by Khatri et al. (2017) examined the instructional innovation strategies used within undergraduate STEM education and compiled a list of 43 strategies intended to enhance the student learning outcomes. These innovative teaching strategies are available for use by STEM instructors in the areas of biology, chemistry, computer science, engineering, geoscience, mathematics, and physics. However, the majority of these teaching strategies are going unused by STEM instructors (Khatri et al., 2017).

Some studies suggest including entrepreneurship as a standard component of the STEM education system. This can be done by engaging business leaders, students, and educators either within or outside of the classroom in an effort to enhance students' soft skills competencies. In these activities, all key stakeholders – the educator, employer, and student – work together on a real-world problem within an active project-based team environment. This practice allows students to learn how to combine their technical and soft skills competencies in order to deliver a product or project that corresponds with the demands of the workplace (Besterfield-Sacre et al., 2014; McKenna et al., 2014).

Prior research shows that despite the importance of soft skills competencies as a significant variable in employability (Sarkar et al., 2016), soft skills are not being prioritized nor taught consistently in undergraduate degree programs. This finding supports a central concern that employers expressed in interviews--that soft skills education is not being given the attention it deserves. 100 percent of employers reported that they value soft skills education and think it is needed for in the future of healthcare.

It takes time to develop soft skills competency. So, by knowing the skills that STEM undergraduate students will need in the future, key stakeholders will be better equipped to focus on this market demand and consequently produce workforce-ready graduates. This development process should begin with lessons about leadership, as employers suggested, starting at the freshman level. On that front, employers also indicated that colleges and universities should offer leadership courses to help develop the soft skills of leadership. This realm of knowledge should begin with self-leadership, team leadership, problem-solving, communication, and critical thinking. Towards the final years of students' undergraduate careers, they should be exposed to classes that aim to provide softs skills that equip them with the knowledge and confidence to conduct their employment searches professionally. Examples of skills within this category are resume building, interviewing, and ultimately securing a job.

ISSN: 2149-8504 (online)

The findings of this study indicate that an open system does not exist between businesses and academic leaders. This lack of collaboration therefore stunts the community's ability to address soft skills gap at its core. In an open system, organizations are actively engaged in relationships that allow them exchange information. It is precisely this disconnect, or lack of an open system, that is impeding the development of soft skills in undergraduate STEM students. The data from this study indicates that much more work is needed to develop an open system in which organizational outputs align with renewed organizational inputs, thus leading to organizational transformation.

Instead, a synergy is needed to tackle the soft skills gap. Employers need to connect with academia and their internal customers to build engagement and customer advocacy to help establish an active collaboration synergy. Both sides need to lead by example to cultivate a culture of support that recognizes and addresses the soft skills gap. Universities that choose to integrate soft skills into undergraduate STEM courses need to understand the skills that are expected of students, how these skills can be transferred into the workplace, and why this development is essential for students' career successes. Without this understanding, as one employer stated, the rapid development of technology will ensure we will be "outdone by the machine."

Future directions

Because the opinions of academic leaders are also instrumental in addressing the soft skills gap, future researchers should consider conducting a similar study to illuminate the perspectives in academia. This research should focus on how educators are collaborating with employers to address the soft skills gap. It would also be enlightening to conduct a study to determine whether STEM educators are equipped to teach and improve soft skills literacy within their core STEM programs to achieve the desired outcomes outlined by the local STEM workforce. Furthermore, future researchers may consider conducting a qualitative study to explore recent STEM college graduates' opinions about the STEM workforce's soft critical skills. Since the soft skills gap is a global issue that needs to be addressed systematically, a final recommendation would be to replicate this study in industries and communities across the US and beyond.

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Journal of Research in STEM Education
Vol 7, No 1, July 2021, 47-68
https://doi.org/10.51355/jstem.2021.102

RESEARCH REPORT

Assessing Robotics Skills in Early Childhood: Development and Testing of a Tool for Evaluating Children's Projects

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Abstract: *Children's robotics skills can be assessed in various ways, one being examining the unique projects that they create. This paper discusses the multi-phase development and testing of a robotics project rubric. The rubric considers both the programming concepts and the aesthetic design elements of a project, which enables researchers and practitioners to determine the overall level of complexity exhibited in the robotics project. This paper presents the background literature and theoretical framework that contributed to the rubric design and summarizes findings from iteratively developing and testing the rubric with a total of 173 robotics projects. Implications for future research and practice are also discussed.*

Keywords: *Rubric, project-based assessment, programming, robotics, early childhood*

Introduction

Ever since Seymour Papert and colleagues' invention of the LOGO turtle in the late 1960s, there has been an increasing focus on the possibilities for robotics to transform young children's thinking and learning. Although shocking at the time, Papert's constructionist ideas about children actively producing and sharing their own technological artifacts are now widely embraced in today's increasingly digital and global society (Bers, 2020; Papert & Harel, 1991). To date, there are over 34 computational kits targeted for children under the age of seven, many of which are physical robots with tangible programming components (Yu & Roque, 2018). One

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To cite this article: Govind, M. & Bers, M. (2021). Assessing robotics skills in early childhood: Development and testing of a tool for evaluating children's projects. *Journal of Research in STEM Education, 7*(1), 47-68. https://doi.org/10.51355/jstem.2021.102

ISSN: 2149-8504 (online)

important reason for the popularity of tangible robotics kits is the opportunity to extend the long-lasting tradition of hands-on learning with manipulatives in early childhood education (Bers, 2008; O'Malley & Fraser, 2004; Resnick, 2007). Studies have identified benefits to introducing robotics at an early age, such as making children's learning visible, sparking interest in coding, and supporting STEAM (Science, Technology, Engineering, Arts, and Mathematics) integration (Benitti, 2012; Bers et al., 2013; Horn & Bers, 2019). With the growing popularity of robotics for young children and the advancement of developmentally appropriate robotics kits, there is a need to understand what children can learn from using and creating with these technologies.

Children's learning of and through robotics can be assessed using various methods, such as multiple-choice questionnaires, design scenarios, artifact-based interviews, and project analyses (Brennan & Resnick, 2012). There are benefits and limitations to each method. For example, questionnaires allow for standardization and measurement of discrete skills. Design scenarios and artifact-based interviews are subjective measures but allow for more nuanced assessment of children's conceptual understanding. Project analyses offer insight into the conceptual encounters a child may experience over the course of designing their project; however, encounters do not necessarily equate to mastery. Because of the varying strengths and limitations of each approach, many researchers often recommend using a "system of assessments" (Grover, 2017) to provide a more holistic understanding of children's knowledge. However, quantity should be paralleled with quality. Assessments must be developmentally appropriate (in this case, for young children) and demonstrate purposeful value for research and practice.

This paper presents work that fills a gap in assessment approaches for robotics kits for young children, most specifically, KIBO, which is a screen-free robot that young children program using tangible wooden blocks and personalize using arts and crafts materials and that is been used worldwide (Albo-Canals et al., 2018; Bers et al., 2019; Jurado et al., 2020). Studies have shown that children as young as three can play with KIBO to acquire foundational coding, robotics, and computational thinking skills (Elkin et al., 2016; Relkin et al., 2020; Sullivan et al., 2017). Current assessment approaches include multiple-choice oral questionnaires such as KIBO Solve-Its and KIBO Mastery Challenges (Hassenfeld et al., 2020; Sullivan & Bers, 2015); artifact-based interviews (DevTech Research Group, 2019; Portelance & Bers, 2015); and design scenarios such as the TACTIC-KIBO Assessment and the KIBO Coding Stages Assessment (Relkin & Bers, 2019; Bers, 2019). Although general assessment rubrics were devised in the past to accompany KIBO lessons and support educators in assessing final KIBO projects (DevTech Research Group, 2018), these rubrics lacked specific scoring criteria and adequate psychometric properties that are necessary for more widespread use in research and educational settings. Thus, the KIBO Project Rubric was developed and is presented in this paper.

The KIBO Project Rubric is a project-based assessment that can be used to examine the level of complexity of programming concepts and design elements exhibited in a KIBO robotics project. This rubric can be adapted to be used with other robotic kits for children. First, this paper summarizes the background literature and theoretical framework that contributed to the rubric design. Second, the paper details the multi-phase, iterative process used to develop and test the rubric with a total of 173 KIBO projects and multiple raters. Finally, the paper presents findings from the development and testing process and discusses the implications and limitations of this rubric in regard to future research and practice use.

Background

Studies on young children's experiences with robotics reveal a variety of benefits for children's learning and development. For instance, learning robotics at a young age can support meta-cognitive thinking and problem-solving skills, referred to in the field as computational thinking (Barr & Stephenson, 2011; Clements & Gullo, 1984; Kafai & Burke, 2014; Seiter & Foreman, 2013; Wing, 2006). Children as young as four and five have shown increased understanding of algorithms, control structures such as repeat loops, and debugging strategies after participating in introductory robotics and programming activities (Elkin, Sullivan & Bers, 2016; Strawhacker & Bers, 2019; Wohl, Porter & Clinch, 2015). Early exposure to robotics, as well as other programmable technologies, may also shape attitudes and help dismantle gender stereotypes about the computing field (Sullivan, 2019).

In addition to robotics as a tool for engaging with coding and computational thinking concepts, there are unique benefits of robotics as tangible programming interfaces for early childhood. The term "tangible", first introduced in the mid-1970s by Radia Perlman with her work on the TORTIS Slot Machine for young children, refers to interfaces that use physical objects and surfaces to manipulate and represent digital information. Physical manipulatives such as screen-free robotics kits promote playful, developmentally appropriate practices already prioritized in early childhood education (Brosterman, 1997; Meacham & Atwood-Blaine, 2018). Several studies have found robotics tools more inviting and engaging to young children as compared to unplugged or screen-based tools (Pugnali, Sullivan & Bers, 2017; Strawhacker & Bers, 2015; Wohl, Porter & Clinch, 2015).

The rubric described in this paper was designed to evaluate projects created with the KIBO robotics kit, a screen-free robotics platform for young children that utilizes tangible programming (Bers, 2020). Children program the KIBO robot by using the barcode scanner embedded in the robot body to scan a series of barcode stickers on tangible wooden blocks. The kit contains sensors, modules, and art platforms so that children can explore more advanced programming concepts, such as repeat loops and conditionals, and use craft materials to decorate their robotic creations (see Figure 1).

ISSN: 2149-8504 (online)

The KIBO robot has been used at large in multiple educational settings all over the world. Studies have shown that children of diverse age groups and abilities have exhibited foundational sequencing and creative problem-solving skills while engaging with KIBO (Albo-Canal et al., 2018; Bers, Gonzalez-Gonzalez, & Armas-Torres, 2019; Sullivan, Bers, & Mihm, 2017; Sullivan, Elkin, & Bers, 2015). Educators have since developed and implemented curricula that integrate KIBO with different content areas, including literacy, math, and social sciences (Elkin, Sullivan, & Bers, 2016; Sullivan, Bers, & Mihm, 2017). However, with coding and robotics education still being a relatively new frontier in early childhood education, there is a need for a reliable project rubric to examine the creative computational artifacts that can be produced with the KIBO robotics kit.

Table 1.

Components of the KIBO Robotics Kit

Category	Components	Image
Hardware	KIBO robot with wheels and motors	
	Input/output modules (Distance, Sound, and Light sensors, Lightbulb, Sound Recorder)	
Software	Begin and End blocks	
	Blue Motion blocks	
	Orange Sound blocks	
	Yellow Light blocks	
	Purple Wait for Clap block	
	Gray Repeat blocks + parameters	

ISSN: 2149-8504 (online)

Category	Components	Image
		
	Lavender If blocks + parameters	
Art platforms	Expression module	
	Stationary or rotating art platform	

Previous rubrics developed for KIBO (DevTech Research Group, 2018) are curriculum-specific and lack specific scoring criteria and adequate psychometric properties that are necessary for more widespread research and practice use. For example, they utilize a 3-point rating scale, in which the differentiating scale markers are labeled as "completely meets", "partially meets", or "does not meet" the stated project requirement. There are between 2-11 different project requirements, depending on the associated lesson topics. Although rating scales can provide some useful information about the level of complexity exhibited in a project, the scoring can often be subjective and requires extensive training for researchers and educators to use effectively with high reliability. In addition to the limitation of subjectivity, these rubrics were designed for existing KIBO curricula that followed a specific lesson structure and format. Thus, its generalizability across other KIBO curricula is unknown, which threatens the rubric's validity.

Alternatives to rating scales are analytic scales and holistic scales. Analytic scales have specific descriptions for each point on a scale, which may be more difficult to develop and ensure adequate psychometric properties, but they may be better suited to use across varied settings. Holistic scales provide a single overall evaluation; these scales are used often in educational settings (e.g., "Satisfactory, Unsatisfactory, Needs Improvement") but provide little-to-no specific feedback unless supplemented with space for descriptive notes. This paper explores these various approaches for assessing KIBO robotics projects in different iterations of the KIBO Project Rubric.

Method

The KIBO Project Rubric was developed using a multi-phase, iterative process. During the first phase of development, scoring criteria were selected based on the general KIBO assessment rubrics (DevTech Research Group, 2018) and other project-based assessment rubrics in the field (e.g., Brennan, Haduong, & Veno, 2020; Grover, 2017; Grover, 2020; Salac & Franklin, 2020). By adapting and remixing existing assessments, similar construct labels were kept consistent and unique characteristics of KIBO were identified and developed into additional scoring criteria. This method for rubric development contributed to the initial face validity of the rubric. This first iteration of the KIBO Project Rubric was tested with N = 123 second graders' KIBO programs recorded using stickers in individual design journals at the end of a 12-lesson KIBO robotics curriculum. After discussing scoring discrepancies and limitations of this first rubric with the research team, a second iteration of the rubric with more nuanced scoring guidelines was developed. This second version was tested with N = 50 KIBO projects documented using videos, pictures, and/or written descriptions. The following sections describe each phase of the development and testing process in greater detail.

Development and Testing Phase 1

The rubric development process began with creating criteria for general and KIBO-specific programming skills. Because KIBO is first and foremost a robotics platform to introduce foundational programming concepts to young children, the first goal was to capture children's conceptual understanding of the KIBO programming blocks. As such, the first iteration of the KIBO Project Rubric consisted of a single holistic 1-5 scale (5 being the highest possible score) guided by five criteria that comprised general programming skills and project characteristics: syntactical accuracy, number of blocks, types of blocks, use of repeat loops/conditionals, and evidence of purposeful programming (see Table 2). Syntactical accuracy referred to whether or not the program would run successfully when executed in the exact manner as written. Number of blocks referred to the total number of KIBO blocks in the program. Types of blocks referred to the variety of KIBO blocks used in the program (apart from the Begin and End blocks), for instance, blue Motion blocks or gray Repeat blocks. The more blocks used with greater variety, the more complex the project. The use of repeat loops and conditionals was the fourth scoring criterion; if used correctly, the project would receive at least a score of 4. The rationale was that the presence of these advanced programming blocks might indicate a child's more advanced understanding of the KIBO robotics kit. The final criterion was evidence of purposeful programming, that is, if there was any written or pictorial evidence from the child's design journal that the blocks were meaningfully related to their final project idea. An example of purposefulness is the use of the Beep block to represent a car honking its horn.

ISSN: 2149-8504 (online)

Table 2.

First Iteration of KIBO Project Rubric with Single Holistic Scale

Score	Level of Project Complexity	Syntactically Correct	Number of Blocks	Types of Blocks	Repeats / Conditionals	Purposefulness
1	Budding	No	-	-	-	-
2	Developing	Yes	<=5	1	No	-
3	Proficient	Yes	>5	1-2	No	-
4	Advanced	Yes	>5	2+	Yes	-
5	Distinguished	Yes	>5	2+	Yes	Yes

Before this rubric was tested with KIBO projects, five experts in early childhood technology with extensive KIBO research and training experience reviewed the rubric and provided feedback, which contributed to the construct validity of the rubric. Their feedback led to several changes to the rubric and its format. For instance, the rubric was digitized into an online Google Form so that scores would be automatically populated into a spreadsheet for analysis. Several checkbox-style items were also added in order to capture the source of syntax errors (e.g., incorrect use of Begin or End block, misplaced or missing Begin or End Repeat/If block, misplaced or missing parameter, etc.). The goal was that these added questions would provide a deeper understanding of children's conceptual encounters and possible misconceptions of key KIBO programming concepts.

This rubric was tested with $N = 123$ KIBO projects recorded in individual design journals with stickers representing the various KIBO programming blocks (see Figure 1). These KIBO projects were completed at the culmination of a 12-hour second grade coding, robotics, and literacy curriculum that was implemented in eight elementary schools in a Virginia public school district. To score these KIBO projects, a research assistant was trained on the rubric. 15% of the projects were jointly scored by two raters to establish agreement and resolve any scoring discrepancies. There was 96% agreement in scores between the two raters.

Figure 1. KIBO Programs Recorded Using Stickers in Students' Design Journals

Percentage agreement was considered to be an appropriate method for assessing reliability at this point in the development process, as several rubric limitations had already been revealed, requiring the need for further revision and retesting. One limitation was the inability to capture the full breadth of KIBO robotics projects from sticker programs alone. For instance, the modules and sensors attached to the robot were unable to be examined, as well as the ways in which the robot was decorated or personalized. These robot characteristics were difficult to assess from design journals but represent a critical component of KIBO robotics projects. Further testing was indeed necessary and required looking at projects that were documented with videos and pictures. Another limitation was that projects were penalized for syntactical inaccuracy, even if advanced programming concepts were attempted. In order to remedy this limitation, the single holistic scale was expanded into an analytic scale with descriptors for each criterion. These individual scores could then be consolidated into a holistic score that would represent the overall level of complexity exhibited in the robotics project. This next section describes this revised rubric development and testing procedure.

Development and Testing Phase 2

The second version of the KIBO Project Rubric consisted of two sets of scoring criteria: (A) Programming Concepts and (B) Project Design Elements. Programming Concepts refer to foundational skills and concepts that are specific to the activity of programming. The five sub-categories of Programming Concepts are (A1) syntactical accuracy, (A2) repeats, (A3) conditionals, (A4) module use, and (A5) data. Project Design Elements refer to project characteristics that add aesthetic appeal, display originality and creativity, or extend the complexity of the project. The five sub-categories of Project Design Elements are (B1) sequencing, (B2) block variety, (B3) robot customization, (B4) setting, and (B5) coordination.

Figure 2 displays the rubric with descriptions of these ten criteria, each of which were scored on a 0-4 scale with individual descriptors for each score on the scale. The higher the points for a particular construct, the more advanced skill exhibited by the project creator. The maximum score for each set of scoring criteria was 20 points. However, when computing a final score for the project, the scores for Programming Concepts and Project Design Elements were weighted differently. Although KIBO offers ample integration opportunities and has aesthetic appeal, its primary educational purpose is to introduce foundational programming concepts to young children. Thus, this rubric utilized a 60-40 weighted ratio, with emphasis given to Programming Concepts by multiplying its summed score by 1.5. Therefore, the maximum number of points for Programming Concepts was 30 points, which brought the total summed score to a maximum of 50 points. Because there was no existing evidence that could be used to determine specific cutoff points for different levels of project complexity, this total score was then categorized evenly into five levels: Budding (0-9 points), Developing (10-19 points), Proficient (20-29 points), Advanced (30-39 points), and Distinguished (40-50 points).

Rubric Criteria

	0 points	1 point	2 points	3 points	4 points
A. Programming Concepts					
A1. Syntactical Accuracy	**No program** created	Nonfunctional program due to **missing Begin/End block**	Nonfunctional program due to **missing or misplaced Begin/End Repeat or If blocks**	Nonfunctional due to **missing or misplaced parameter**	**Functional** program created
A2. Repeats	**No repeat blocks** used	Repeat attempted but **missing or misplaced the Begin/End and/or parameter** or **no blocks in-between Begin/End blocks**	**At least one successful repeat loop** with number parameter	**At least one successful repeat loop** with sensor parameters	At least one successful repeat loop as part of **nested statement**
A3. Conditionals	**No If blocks** used	Conditional attempted but **missing or misplaced the Begin/End and/or parameter**	Conditional attempted correctly but **no blocks in-between Begin/End blocks**	**At least one successful conditional statement** with sensor parameter	At least one successful conditional statement as part of **nested statement**
A4. Module Use	**No modules attached** to the KIBO body	**No correspondence** or **only wheels/motors attached**	**At least one module with correspondence** to the program (in addition to wheels and motors)	**All attached modules are purposeful** and correspond to the constructed program	All attached modules are purposeful **and activated purposefully** when program is running
A5. Data	**No use of sound recorder**	**Sound recorder used incorrectly** (no sound)	**One successfully recorded sound** with sound recorder	**2+ successfully recorded sounds** with sound recorder	**Subroutines** used correctly
B. Project Design Elements					
B1. Sequencing	**3 or fewer blocks** used	**4-5 blocks** used	**6-9 blocks** used	**10-14 blocks** used	**15+ blocks** used
B2. Block Variety	No program or **only Begin/End blocks** used	**1 type** of block used	**2-3 different types** of blocks used	**4-5 different types** of blocks used	**6 types** of blocks used (blue, yellow, orange, gray, lavender, purple)
B3. Robot Customization	**No customization or decorations**	Use of existing KIBO extension modules (ex. platform) as decoration; **no personalized customization**	**1 piece of decoration** added; simple customization	**Personalized arts & crafts and/or building materials** attached to robot	**Highly** personalized arts & crafts and/or building materials **securely attached** to robot
B4. Setting	**No other project elements** added	**1 other project element** added (apart from robot/program)	**2 other project elements** added (apart from robot/program)	**3 other project elements** added (apart from robot/program)	**4+ other project elements** added (apart from robot/program)
B5. Coordination	**No background music or dance, Wait for Clap block, or use of multiple robots**	Used **Wait for Clap block as the final block** before End; no synchronized music or dance	Used Wait for Clap block in **middle of the program**; background music or dance does not fully match program	**Used background music/dance strategically** to match program	**Multiple KIBO robots running synchronously** with background music or dance

Step-by-Step Scoring Guide

Step 1:	**Step 2:**	**Step 3:**	**Step 4:**
Add up all of the A scores: ____ out of 20 Then multiply by 1.5: ____ **out of 30**	Add up all of the B scores: ____ **out of 20**	Add scores from Steps 1 and 2: ____ **out of 50**	Identify project's level of complexity: ☐ **Budding (0-9)** ☐ **Developing (10-19)** ☐ **Proficient (20-29)** ☐ **Advanced (30-39)** ☐ **Distinguished (40-50)**

Figure 2. Second Iteration of the KIBO Project Rubric with Analytic and Holistic Scales

This revised rubric was tested with N = 50 KIBO projects that were documented using videos, pictures, and/or written descriptions. In order to include the project in our analytic sample, both the block program and the physical KIBO robot needed to be visible. To find projects that fit this inclusion criterion, we used KIBO project videos from earlier research projects and professional development trainings collected by the research team over a number of years, as well as projects that were publicly shared online. This convenience sample included KIBO projects created by young children, as well as adult educators and practitioners. No names were associated with projects; the only recorded characteristic was whether the project was created by an adult or child. The final analytic sample consisted of 25 adult-created and 25 child-created projects.

ISSN: 2149-8504 (online)

This revised rubric went through a similar process of iteration and testing. The same team of KIBO experts provided feedback, resulting in minor wording adjustments. To test the rubric, one researcher (Rater 1) scored all 50 projects and trained a second researcher (Rater 2) on the rubric, who also scored all 50 projects. The two raters participated in four rounds of check-ins (after 10, 25, 37, and 50 projects were scored) to assess inter-rater reliability, review scoring discrepancies, and accordingly revise the wording of rubric criteria for better clarity. Multiple inter-rater reliability measures were computed at every check-in. In addition to percentage agreement, weighted kappas using linear weights for the ten scoring constructs and the overall project score were computed. Weighted kappas were used instead of intra-class correlation or other measures because there were two independent raters for the entire dataset, and all 11 variables were treated as ordinal scales (Cohen, 1968; Fleiss & Cohen, 1973).

The next section details the findings from the two phases of rubric testing. Findings include descriptive from both analytic samples (*N* = 123 projects for the first rubric and *N* = 50 projects for the second rubric), as well as results from inter-rater reliability analyses for the second analytic sample. Three examples of KIBO projects are also included to demonstrate the rubric's face validity and showcase how the projects' varying levels of complexity were reflected in their KIBO Project Rubric scores. Because of the broad inclusion criteria for projects and the many variables that play a role in the design process of KIBO projects (e.g., nature of the robotics activity, time and space allocated for participants, type of KIBO kit, arts and crafts materials available, etc.), no between-participant nor adult-child comparative analyses were conducted. All performed analyses were done using SPSS Statistics Version 27.

Results

Descriptives

For the first version of the KIBO Project Rubric, the average project score was 2.41 (*SD* = 1.11) out of a possible 5 points. The overall complexity of projects varied: 39 students' projects (31.7%) were classified as Budding, 14 (11.4%) as Developing, 51 (41.5%) as Proficient, 18 (14.6%) as Advanced, and one (0.8%) as Distinguished. The majority of students did not use a repeat loop (60.5%) or a conditional statement (89.1%) in their KIBO programs. Further syntax analysis indicated that of the 58 students who used a repeat loop, 24 students (41.4%) used it correctly. Of the 16 students who used a conditional statement, 7 of them (43.4%) used it correctly. Over a quarter of students' final programs (35.4%) were syntactically incorrect, almost all of which exhibited errors with repeat loops, conditionals, or their corresponding parameters.

ISSN: 2149-8504 (online)

For the second version of the KIBO Project Rubric, the average project score was 24.42 (*SD* = 6.56; range = 11-39) for Rater 1 and 23.91 (*SD* = 5.80; range = 10.5-38) for Rater 2 out of a possible 50 points. The average deviance between the two raters' numerical scores was 1.93 points (*SD* = 1.58). Deviance ranged from 0-7 points. For Rater 1, 15 projects were classified as Developing, 26 projects as Proficient, and 9 projects as Advanced. For Rater 2, 11 projects were classified as Developing, 32 projects as Proficient, and 7 projects as Advanced. None of the 50 projects received a Budding or Distinguished score. Independent samples *t*-tests and a Chi-square analysis indicated no significant difference ($p > .05$) between Rater 1 and 2 in projects' overall numerical scores, sub-scores for Programming Concepts and Project Design Elements, or overall level of complexity. Figure 3 displays the histogram for all 100 scores from both raters, showing a normal distribution.

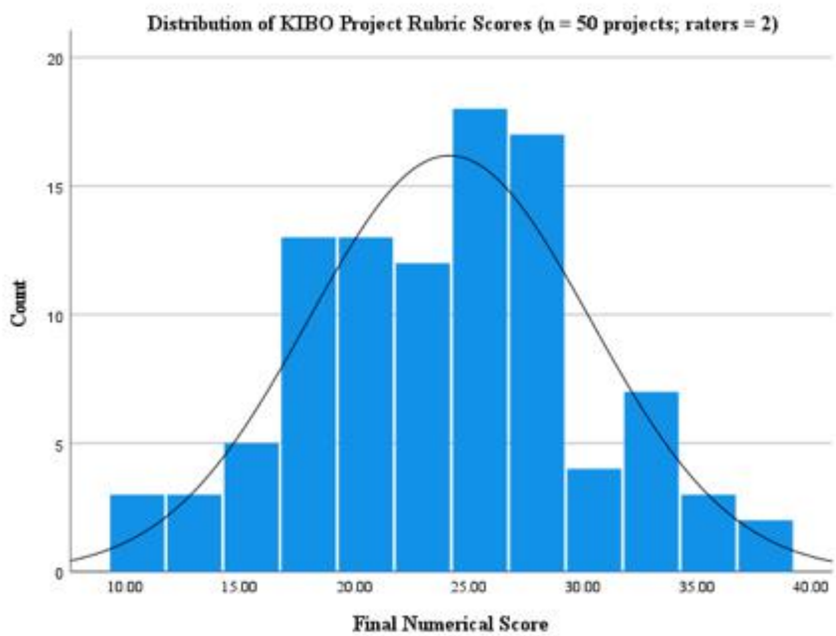

Figure 3. Normal Distribution of KIBO Project Rubric Scores

Reliability

The reliability findings focus on the second iteration of the rubric. Table 3 displays the inter-rater reliability at each of the four rounds of check-ins between the two raters for all ten scoring criteria (A1, A2, A3, A4, A5, B1, B2, B3, B4, and B5). Percentage agreement ranged from 73-77%. Weighted kappa's using linear weights ranged from .802-.838 ($p < .001$), which indicates statistically significant agreement between the two raters. The strength of agreement can be classified as strong agreement beyond chance (Cicchetti & Allison, 1971; Fleiss, Levin & Paik, 2003).

ISSN: 2149-8504 (online)

Table 3.
Inter-Rater Reliability for Overall KIBO Project Rubric Scores (N = 50 projects)

Round of Analysis	Percentage Agreement (%)	Weighted Kappa Using Linear Weights (κ_w)
Round 1 (after 10 projects)	76.0	.805, $p < .001$
Round 2 (after 25 projects)	74.3	.802, $p < .001$
Round 3 (after 37 projects)	72.7	.813, $p < .001$
Round 4 (after 50 projects)	77.4	.838, $p < .001$

When each of the ten scoring criteria were analyzed separately for inter-rater reliability, it was evident that some criteria were easier to agree upon than others. Table 4 depicts the weighted kappas using linear weights for each criterion. Block Variety (B2) and Setting (B4), in particular, had poor agreement between the two raters, $\kappa_w < .4$. Module Use (A4) and Coordination (B5) had fair inter-rater agreement, $\kappa_w < .75$. The remaining six criteria had strong inter-rater agreement, $\kappa_w > .75$.

Table 4.
Inter-Rater Reliability for Individual KIBO Project Rubric Criteria (N = 50 projects)

Rubric Criterion	Weighted Kappa Using Linear Weights (κ_w)
A1. Syntactical Accuracy	.851, $p < .001$
A2. Repeats	.905, $p < .001$
A3. Conditionals	.904, $p < .001$
A4. Module Use	.593, $p < .001$
A5. Data	.814, $p < .001$
B1. Sequencing	.935, $p < .001$
B2. Block Variety	.118, $p = .077$
B3. Robot Customization	.764, $p < .001$
B4. Setting	.267, $p < .001$
B5. Coordination	.671, $p < .001$

Percentage agreement and weighted kappa were also computed for the projects' overall level of complexity (Budding, Developing, Proficient, Advanced, and Distinguished). Percentage agreement for the 50 projects was 84%. The eight projects with varying levels from the two raters did not differ by more than one level (e.g., Developing versus Proficient). Weighted kappa using linear weights (κ_w) was .757, $p < .001$, which indicates statistically significant and strong agreement between the two raters (Cicchetti & Allison, 1971; Fleiss, Levin & Paik, 2003).

Validity

The KIBO Project Rubric has adequate face validity, which was established from adapting the rubric criteria from assessments of other coding and robotic technologies for children (e.g., Scratch, ScratchJr, Bee-Bot, etc.). Feedback from the five KIBO experts also supported rubric improvement, particularly in terms of defining key programming concepts. For instance, experts' questions included, “How is correspondence defined?”, “What does it mean for all attached modules to be purposeful?”, and “I think it will be helpful to mention that the block types can be distinguished by color.” Expert review also contributed to content validity of the rubric, which was further enhanced with the additional Project Design Elements set of criteria. To demonstrate the rubric’s face validity, three illustrative examples of children’s KIBO robotics projects are presented.

Project Example 1. Figure 4 displays a kindergarten classroom implementing a KIBO robotics curriculum, in which two students were working together on their final KIBO project. Their program reads, “Begin, Sing, Beep, Shake, Wait for Clap, Red Light On, End”, and affixed to their robot are a lightbulb and sound sensor. The students created a syntactically correct and functional program (A1. 4 points) but did not use any repeats (A2. 0 points) nor conditionals (A3. 0 points). All of the modules attached to the robot—the wheels and motors, lightbulb, and sound sensor—are used and activated purposefully with specific correspondence to the Shake, Red Light On, and Wait for Clap blocks, respectively (A4. 4 points). There is no evidence of data storage in this program (A5. 0 points). Thus, the total sub-score for Programming Concepts is 8 points; when weighted 1.5 times, the sub-score is 12 points. When examining the Project Design Elements of this project, there are a total of seven blocks in this program (B1. 2 points), which include four different types of blocks: orange Sound, blue Motion, purple Wait for Clap, and yellow Light blocks (B2. 3 points). There are no decorations secured to the robot (B3. 0 points) nor other aesthetic elements surrounding the project (B4. 0 points). There is some evidence of coordination because of the placement of the Wait for Clap block in the middle of the KIBO program (B5. 2 points). The total sub-score for Project Design Elements is 7 points, bringing the total numerical score to 19. Thus, this project displays a Developing level of complexity.

Figure 4. KIBO Robotics Project Example 1

ISSN: 2149-8504 (online)

Project Example 2. Figure 5 displays another kindergarten classroom that utilized the storybook *Brown Bear, Brown Bear, What Do You See?* by Bill Martin, Jr. and Eric Carle as the theme for their KIBO projects. A kindergarten student designed and programmed his KIBO robot to move through the taped illustrations, which depict the brown bear going to a farm and seeing a white dog. The KIBO program reads, "Begin, White Light On, Repeat, Three, Forward, Turn Left, End Repeat, End". Affixed to the robot are wheels and motors, as well as the lightbulb module and art platform that holds the student's personalized brown bear decorations. The program has no syntactical errors (A1. 4 points) and successfully utilizes a repeat loop with a number parameter (A2. 2 points). No conditionals are used (A3. 0 points). All attached modules are used purposefully, but because the program does not utilize any sensors, there is no purposeful activation (A4. 3 points). There is no evidence of data storage in this KIBO program (A5. 0 points). The total sub-score for Programming Concepts is 9 points; when multiplied by 1.5, the weighted sub-score is 13.5 points. With respect to the Project Design Elements, there are a total of eight blocks in this program (B1. 2 points) of three different types: yellow Light, gray Repeat, and blue Motion blocks (B2. 2 points). The robot's decorations are highly personalized, using various kinds of arts and crafts materials (B3. 4 points). The project's setting includes three distinct pieces of artwork taped to the floor, which are integral components of the book-themed project (B4. 3 points). Finally, there is no evidence of coordination in the form of multiple robots moving simultaneously, use of background music, or the Wait for Clap block (B5. 0 points). The total sub-score for Project Design Elements is 11 points, bringing the total numerical score to 24.5. Thus, this project receives a Proficient level of complexity.

Figure 5. KIBO Robotics Project Example 2

ISSN: 2149-8504 (online)

Project Example 3. Figure 6 displays a KIBO project created by a second-grade student. The constructed block sequence, which reads "Begin, Repeat, Three, If, Light, White Light On, Red Light On, Blue Light On, End If, If, Dark, Wait for Clap, Wait for Clap, Forward, End If, End Repeat, End", is syntactically correct (A1. 4 points). There are two consecutive conditional statements inside of a repeat loop, demonstrating the child's ability to sequence a nested statement (A2. 4 points and A3. 4 points). Although not all the modules are displayed in this photo, supporting video documentation indicated that the child had appropriately affixed the wheels and motors, light sensor, lightbulb, and sound sensor to her robot. However, when the child was testing the KIBO program, she had trouble with triggering the light sensor with the flashlight; thus, the light sensor was not successfully activated (A4. 3 points). There is no use of data storage in this project (A5. 0 points). With respect to the project's design elements, the child used more than 15 blocks (B1. 4 points) of 5 different kinds (B2. 3 points). There is no customized decoration apart from the existing platform extension (B3. 1 point). The flashlight, which was used to trigger the light sensor, is considered part of the setting (B4. 1 point). Finally, the Wait for Clap blocks are placed intentionally inside one of the conditional statements (B5. 3 points). Altogether, this project receives 15 points for Programming Concepts (weighted to 22.5 points) and 11 points for Project Design Elements, which brings the total number to 33.5 points. Overall, this project displays an Advanced level of complexity.

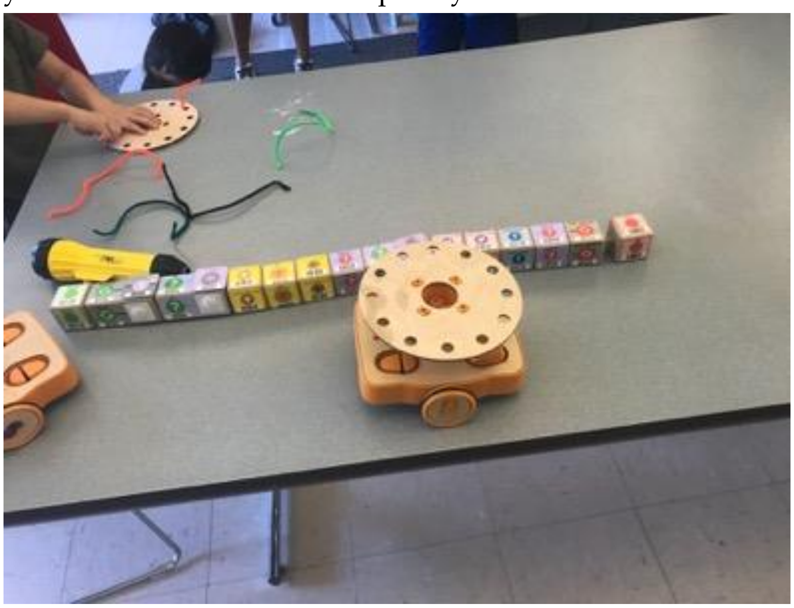

Figure 6. KIBO Robotics Project Example 3

The picture and video documentation of these example projects were useful in determining each project's level of complexity. From the pictures alone, it is evident that the second example contains more aesthetic project elements than the first example. This second example also utilized a repeat loop, which is a more advanced programming concept. Thus, it is not surprising that this second project received a higher numerical score and overall level of project complexity in comparison to the first project. However, one area in which the first example surpassed the second is the Module Use criterion. The use of the sound sensor and Wait for Clap block in the first project demonstrates an advanced understanding of KIBO sensors, which was not evident in the second project that only utilized the lightbulb module. Although barely decorated, the third example project displayed skillful use of repeat loops and conditional statements, which contributed to its high score. As shown in these three examples, there are many different components of KIBO robotics projects, which were captured by the various criteria in our KIBO Project Rubric.

Discussion

Early childhood robotics learning has become an increasing focus of early computer science and STEAM education efforts. The screen-free KIBO robotics platform is one such technological tool that engages young children in foundational programming concepts while also promoting creativity, self-expression, and design thinking. Although there are various assessments for children's KIBO learning (DevTech Research Group, 2019), these assessments fall under the category of multiple-choice questionnaires, interview protocols, and design scenarios. There are no KIBO rubrics for assessing young children's robotics projects with adequate psychometric properties. This paper filled this gap by presenting the multi-phase development and testing process of the KIBO Project Rubric, a project-based assessment tool for the KIBO robotics platform. Using a total of 173 KIBO projects, 123 of which were recorded in student design journals and 50 of which were recorded using picture and video documentation, the psychometric properties of the KIBO Project Rubric were explored, and the rubric was iteratively improved in its design and format.

This discussion primarily focuses on the second version of the KIBO Project Rubric, as this rubric provides a more comprehensive examination of KIBO project artifacts. However, the first rubric, which consisted of a single 5-point scale, might still be a suitable assessment tool if the goal is to focus specifically on the KIBO programming language (i.e., the block program). In that case, this rubric would be relatively quick to administer and would foster insight into students' depth of understanding and application of programming concepts in their constructed codes. For instance, findings indicated that children were unlikely to utilize repeats and conditionals in their KIBO projects, even if they engaged in those topics in a full-length KIBO curriculum. The majority of children who did use these advanced KIBO blocks exhibited syntax errors (e.g., missing a Begin or End Repeat/If block or the proper corresponding parameter). There may be a number of reasons for these errors, such as students being unable to record their programs accurately using the KIBO stickers, not having enough time to check over their work, or not fully understanding

ISSN: 2149-8504 (online)

how these advanced concepts are used. If the latter reason is true, then this is further reason to promote the use of multiple assessments to understand the full extent of children's programming knowledge. Prior research has showed that kindergarten, first, and second grade students performed equally well on advanced programming KIBO Solve-Its, which included questions about repeats and conditionals (Sullivan & Bers, 2015). Perhaps it may be that children can correctly answer questions about these advanced programming concepts but do not exhibit this knowledge when given the opportunity to apply these concepts in their projects. Further research is needed in this area to explore how children may exhibit their programming knowledge using various assessment methods.

The rubric development and testing process reemphasized the notion that programming is only one aspect of a robotics project. Because of the customizable art platform and the various aesthetic elements that can be added to make KIBO robotic creations come alive, there was a need to expand the KIBO Project Rubric to include these design elements. Thus, if the goal is to examine KIBO robotics projects in their entirety, the second iteration of the KIBO Project Rubric is a more suitable assessment tool. Overall, this rubric demonstrated good psychometric properties. Multiple forms of validity (e.g., construct, content, and face validity) were investigated. Further rubric validation is required, perhaps by inviting teachers to use the rubric to assess students' KIBO projects and comparing their ratings to researchers' ratings of the same projects.

Findings from inter-rater reliability analyses indicated strong agreement beyond chance between the two raters. However, there were four criteria with low-to-medium inter-rater agreement: Block Variety (B2), Setting (B4), Module Use (A4), and Coordination (B5). What might be the source of these discrepancies? About halfway through scoring, it became known that the two raters disagreed on whether the Begin and End blocks should be considered as a type of block. It was then clarified that the Begin and End blocks do not count for this criterion. In addition, Setting, Module Use, and Coordination were sometimes difficult to assess, depending on the quality of picture or video documentation. Perhaps these discrepancies may be resolved if KIBO projects are documented thoroughly to display all aspects of the program and the robot. Video documentation, in particular, might be more suitable, especially if the project contains background music, or if the child is narrating their project idea in the background. To remedy some of the scoring discrepancies and further improve the reliability of the KIBO Project Rubric, examples for each 0-4 marker for each of the ten scoring criteria were added. This third and current version of the KIBO Project Rubric (available online at http://bit.ly/kibo-project-rubric) will be retested in future work and reexamined for its psychometric properties. Guidance on documentation should also be provided to assessors, specifying that project documentation should include the KIBO block sequence, physical robot in its decorated form, and a video of the robot in action.

ISSN: 2149-8504 (online)

There are several important points to note about the rubric's final project scores. One is the positive framing for the names of the five level categories. Aligned with the principles of strengths-based education (Lopez & Louis, 2009), the level of project complexity obtained from the KIBO Project Rubric is meant to highlight the strengths of project creators' efforts and achievement, rather than position any misconceptions in their learning as deficits. Positive framing also serves to position learning with the KIBO robotics kit as a developmental activity. A person (child or adult) who is introduced to KIBO for the very first time, even if older by age, may not necessarily create a "proficient" project. By using the terms "budding" or "developing", the rubric acknowledges that each project creator is growing their programming skills and with more experience and exposure, they may have the opportunity to produce more complex KIBO projects.

It is also essential to note that the final score does not indicate overall level of programming mastery. Rather, the score provides an estimated level of mastery *as exhibited in this particular project*, which means that projects might be limited by factors outside of their control. For example, children who are working with KIBO-10 (an introductory kit containing the 10 basic programming blocks) are likely to create projects that are less complex than children working with KIBO-21 (a more comprehensive kit with additional advanced blocks and sensors). Unless children are prompted to demonstrate their most advanced programming skills in their projects, as well as provided with unlimited time and resources for building and decorating their robots, children would not be expected to display the full extent of their knowledge in a single project. Thus, a limitation of a project-based assessment is that it is only one way of understanding children's KIBO knowledge. Another limitation is that half of the second analytic sample examined adult-created projects. Although no adult-child comparative analyses were presented in this paper, future work may explore the level of complexity exhibited in adults' KIBO projects in comparison to children's KIBO projects, as well as projects created by children of varying age and ability levels.

Conclusions

This paper presents the multi-phase development and testing for a robotics project rubric. Key lessons were learned in this process, such as documenting both process and outcome of robotics projects, acknowledging possible subjectivity and ambiguity in scoring project artifacts, and emphasizing projects' creative intent as much as exhibited content knowledge. The findings of this paper, as well as these lessons learned, can be used to inform the development of rubrics for other robotics platforms for young children. For example, robotics projects with Bee-Bot® or Code-a-Pillar™ also involve both programming and aesthetic design elements that could be assessed to shed insight into children's learning. In addition, the process through which the KIBO

ISSN: 2149-8504 (online)

Project Rubric was developed and tested reveals the iterative nature of rubric design. This method is essential because any artifact with practical use in both research and educational settings should be developed iteratively with feedback from researchers and practitioners. Future work for the KIBO Project Rubric will continue to seek stakeholder feedback, not only for the rubric, but also for user training and calibration.

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