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Closing the Signaling Gap: leveraging learning science and technology design principles to support marginalized and vulnerable youth to transfer their skills, knowledge, and abilities, to new and different types of work.

Tessa Forshaw
Stanford University
tforshaw@stanford.edu

Sergio Rosas
Stanford University
srosas@stanfordalumni.org

Bethanie Maples
Stanford University
bethanie@stanford.edu

Abstract

The OECD suggests that young people, ages 18-25, will be the hardest hit by the future of work. As entry-level positions are more likely to involve routine tasks with low skill requirements, this group will be most at risk for disruptions or transitions partially because lack of social capital and exposure to careers prevent them from finding the necessary support to transfer their skills to a new environment (OECD, 2018). As society faces an uncertain and changing future of work, workforce development needs a new paradigm; one founded in leveraging the learning sciences and human-centered technology design to drive inclusion.

A preliminary trial of a web-based skills visualization tool with the LA Chamber of Commerce suggests that when participants in their workforce development program created their skills visualization map using the tool, the quantity, and quality of skills used to self-describe increased. Further, the number of participants recommended for an internship also increased. These early results indicate that using a skills visualization map may promote self-explanation, and allow participants to construct a better understanding of how to transfer their skills to a new environment. This approach was used to address the core learning problem of self-explanation, as studies have shown that self-explanation and visualizations are powerful strategies to learn more deeply (Schwartz et al., 2016).

1. Introduction

Our global society is facing a time of great opportunities and challenges with respect to the value of human intelligence. Intelligent automation - and computing technology more broadly - is not only revolutionizing many industries but subsequently disrupting our workforce. Every historical industrial revolution driven by technological change has resulted in job displacement, although never at its current pace and scale. McKinsey estimates that more than 1 billion jobs will be lost due to automation (Manyika, 2017), and the OECD predicts that 10% of jobs can be automated (Arntz, Gregory, & Zierahn, 2016). When automation takes not only individual jobs but eventually *entire professions*, workers cannot simply reapply or upskill; in fact, they will need to reframe their occupation. For example, when self-driving trucks become pervasive, truck drivers will need to find new types of work. The nature of this wave of automation is its replacement of jobs traditionally performed by marginalized and vulnerable youth, putting this population at an even greater risk of disruption and exclusion than in previous generations (OECD, 2018).

One common recommendation made to those facing disruption is that they reskill into an entirely new profession. Yet, according to a job retraining analysis conducted by Amy Goldstein in Wisconsin, workers laid-off from General Motors who subsequently enrolled in community college to reskill into new professions, were 17% less likely to find steady work and earn 40 cents less on the dollar compared to those who did not retrain (Goldstein, 2017). These, as well as similar findings on the efficacy of coding boot camps (Wilson, 2017), illustrate that traditional approaches to "reskilling" are not sustainable and need a new evolution. Unfortunately, US federal funding for on the job employment and training programs has been cut by $1B since 2010 (National Skills Coalition, 2019) and over the last 20 years funding for these programs has decreased by 40% (Conway, 2018). Funding that is available is allocated to outdated training and workforce readiness programs, with very limited resources supporting time to learn and earn on the job.

A significant question must now be faced: how might we support marginalized and vulnerable youth to transfer their skills, knowledge, and abilities, to new and different types of work in the 21st century? This research proposal premises that we leverage the application of learning science to technology design, supporting learners in better understanding how to transfer their knowledge, skills, and abilities to new and different types of work. The first of the three following elements considers a review of the context and literature surrounding the research question. The second, a discussion of our preliminary study that utilizes technology as one possible solution. Finally, the third proposes further opportunities for research.

2. Literature and Context

Skills gap or Signaling gap?

The OECD suggests that young people, ages 18-25 from marginalized and vulnerable populations, will be the hardest hit by the future of work as entry-level positions are more likely to involve routine tasks with low skill requirements that are easily automated. Further, the OECD estimates that this group is not only most at risk of job disruption but also of transitional difficulties (OECD, 2018). We can see this growing shift in global labor markets; the LinkedIn Economic Graph quarterly report (LinkedIn Economic Graph, 2018) highlights what they term a 'growing skills gap' where many low and middle-skill workers have 'skills' that are in great supply but low demand.

Yet, experts speaking at the Shaping the Workforce of the Future (SWF) series, held at Stanford University in 2018, highlighted that workers aged 18-25 from marginalized and vulnerable workforce populations do nott always lack in-demand workforce skills, but rather struggle to realize how they can translate, and therefore tranfser, their skills and experiences beyond their immediate role or industry (SWF, 2018). A finding that is supported by the Los Angeles Area Chamber of Commerce (LA Chamber). The LA Chamber is a workforce intermediary that connects workers aged 18-25 from marginalized and vulnerable workforce populations to job opportunities with 1,600+ businesses in LA County. (De Vivo, Rosas, Arian, Graff, and Heisser, 2017)

Despite the recent resurgence in popularity, discussions about America's growing skills gap are not new. The term was commonly used in the Cold War era to suggest that the educational system was failing to ensure the political and economic stability of America (Hora, Benbow, Oleson, 2016). Blaming the skills gap is a convenient narrative for organizations either facing talent shortages or rationalizing their labor force. This narrative pushes the blame onto individuals in our society for not *having* the 'right' skills, or for the educational system for not *developing* the 'right' skills.

Together, these insights sparked the notion that perhaps the workforce of the future is not facing such a significant "skills gap" but rather a "signaling gap." This is not to suggest that the skills gap does not exist at all, perhaps, however, we might have more success addressing inclusion in the future of work if we reframe the context as a signaling gap. Literature from leading organizations in the skills, workforce, and education sector reinforces this idea. Notably reports by the ACT Foundation (2018), and LinkedIn and the World Bank's Solutions for Youth Employment (2017) also indicate that we are facing such a "signaling gap".

Considering signaling as a representation of a learner's self-awareness of how to transfer their skills to new and different types of work.

Towards the conclusion of the SWF series, the concept of signaling was defined by the collective as the process of a learner communicating to an employer that are cognisant of their prior learning can transfer to new contexts. Transfer starts when learners are able to recognize the similarities between a past experience *x* and new task *y* and then see how to apply learning from *x* to do *y* (Pea, 1987).

Often the ability to transfer, referred to in psychology as *analogical reasoning* (Bartha, 2013), is learned in informal educational environments by "doing it" or observing others. Marginalized and vulnerable populations traditionally have limited exposure to this kind of practice, and are thus potentially less adept in pursuing opportunities to transfer learning. Further, while research from cognitive science and psychology supports that analogical reasoning is a critical skill in education and work, it is rarely performed by learners being documented in laboratory settings (Gick & Holyoak, 1983) (Vendetti, Matlen, Richland, & Bunge, 2015). This suggests that learners, especially those from marginalized and vulnerable youth populations, need additional interventions to further develop the ability to apply previously learned information and skills to new contexts.

Most interestingly, the ACT Foundation (2018) suggests that a signaling gap can be overcome by highlighting an individual's overall competencies rather than discrete skills; an idea which supports redefining discrete skills into broader competencies. According to the U.S Office of Personnel Management (2016), and the United Nations Educational, Scientific and Cultural Organization (2015), a competency is "the capability to apply or use a set of related knowledge, skills, and abilities required to successfully perform critical work functions or tasks in a defined work setting." Competencies are thus considered to be a set of skills, knowledge, and abilities. These are the categories that describe something a person is able to do. Reimers & Chung (2016) see competencies as more comprehensive than skills.

Situative learning practices found in the workforce can help close knowledge gaps left after a learner has transferred their skill from old work to new work.

Many learning scientists advocate that "situated learning is important in part because of the crucial issue of transfer." (Dede, 2010) This perspective suggests that the transfer of skills to new work will be most effective when it is situated in new contexts through cognitive apprenticeship, a community of practice, legitimate peripheral participation, (Collins, & Greeno, 2010) participatory appropriation, guided participation and apprenticeship (Rogoff, 2008). Through this approach, if a learner has strong analogous skills and experience, then through principles of 'learning by doing' (Collins, & Greeno, 2010), theoretically, they could do any job that requires skills that have the same 'common elements' as the ones they have (Brown, Collins & Duguid, 1989).

2. Technology as a potential solution

Closing the signaling gap by prompting self-reflection through learner created visualization.

To test if enabling marginalized and vulnerable jobseekers to see how their skills transfer to new types of work help close the signaling gap and result in gainful work opportunities, a skills visualization technology application was prototyped and tested. Learners use the skills visualization map, by inputting data from their resume and LinkedIn to generate a consolidated view of their skills. After running each skill through a database of over 15,000 skills, the tool produces a visualization of how their skillset maps to the Institute for the Future's, Future Work Skills 2020 framework (2018). This framework was selected after an analysis of more than thirty different future skills frameworks due to its rigorous development methodology (IFTF, 2018) and unique categories that were likely to be unfamiliar to learners. The comprehensive skills library was created by consolidating dozens of skills libraries including LinkedIn and the US Department of Labor's O*Net.

- **Step 1:** The skills visualization tool leverages existing user data to gain the most complete picture of a person in the shortest amount of time. Data is populated via a web application. Currently, the product allows for an upload of a resume (PDF) and a way to access information from a user's LinkedIn account via the API.
- **Step 2:** The skills visualization tool then processes the input data and creates a consolidated and structured view of all uploaded data about an individual. It then analyzes the consolidated profile against its extensive Skills and Competency Corpus to produce a list of Future of Work competencies where the subjects skills correlate.
- **Step 3:** The profile in step 2 is then mapped, using data visualization software, to create a user-friendly visual data map that is unique to the individual. This dynamic and interactive D3 visualization improves a person's ability to see and self-explain their skills and competencies. The output contains two views; a circular map (pictured in Figure 1) that shows all skills as capability areas, sized by frequency and a chart of each competency with more detailed information[1].

[1] The prototype is live and available for use via www.skillsviz.org and the source code is available on bitbucket under an MIT open source license via https://bitbucket.org/phillderesa/skills-visualization-tool.git

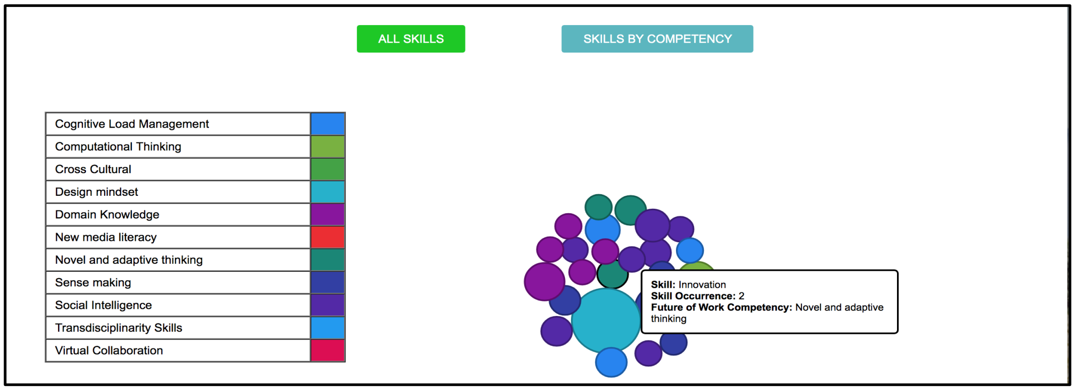

Figure 1: Example learner skills visualization

The decision for visualization as the primary technology is influenced by Stanford GSE Dean Daniel Schwartz's findings that visualization is a strategy for organizing ideas and that it "can help people discover new structures that improve future problem-solving" (Schwartz, Tsang, & Blair, 2016). Moreover, recent research suggests that visualizing relationally corresponding elements of an analogy can help prompt a learner to engage in the process of analogical mapping; a core component of transfer (Matlen, Gentner, & Franconeri, 2014). Additionally, by representing abstract knowledge in concrete form (Sawyer, 2006), it helps learners make meaning by expressing their skills as project external to themselves so that it can be critiqued and evaluated (Popper, 1978).

3. A small preliminary study reveals early findings

Signaling improves job opportunities by a factor of three

Over the course of a year, two core tests were conducted that focused on answering fundamental questions about the usability and efficacy of a skills visualization map: 1) Does a user learn anything from creating a skills visualization map? 2) Does the user consider their skills visualization map helpful? 3) Does using a skills visualization map improve the user's ability for self-explanation and enable a "self-aware transfer state of mind?" (Pea, 1987)

To test this logic, job seekers aged 18 to 26 were targeted from low-income, first-generation, and diverse backgrounds looking for their first internship at a local startup or tech company in the Los Angeles area. These job seekers were sourced through an existing internship program that recruits community college talent in the Los Angeles Area. The LA Chamber agreed to partner with our research team to carry out two tests, with three methods of data collection used: surveys, practice interview voice transcripts, and observation notes.

3.1. Test 1 Snap Design Academy Fellows with the LA Chamber

Methods

A collaboration was formed with the Snap Design Academy (SDA) and the Los Angeles Area Chamber of Commerce (LA Chamber), in a five-week boot camp at Snap, Inc. (formerly Snapchat). The SDA brings together young adults from underserved populations together to learn design thinking and user experience design skills in a maker environment. This study involved collaborating with a staff member from the LA Chamber who was facilitating the SDA program at Snap to complete the study on site with twenty SDA program participants. SDA participants were selected in full by the LA Chamber.

Halfway through the Snap Design Academy program, participants were prompted by a facilitator to generate their unique skills map using the visualization tool by leveraging their LinkedIn profile and their resume. They were provided with five minutes to freely explore their skills visualization before being asked to complete a short survey that included short answer questions on reactions and Likert Scale questions on usefulness and relevance. This survey included the following questions:

- What surprised you about your skills visualization?
- What did not surprise you about your skills visualization?
- What are the strengths that you want employers to know about you?
- What jobs do you feel prepared for?
- Rate how helpful your skills visualization was in understanding your skills

Results

A foundational analysis revealed that 80% of participants found their skills visualization map helpful. Moreover, due to the qualitative nature of the survey, participants shared their reactions, which reinforced and validated skills visualization maps as a useful tool. One student shared, “I was surprised by how my skills could be translated into professional terms that I did not know I had. I always thought that these skills were gained only after being in a professional work environment.”

3.2. Test 2 LA Chamber interviews

Methods

As a way of observing job seekers in an environment where they were deliberately seeking help with their job search, the final test targeted seventeen job seekers participating in practice interviews for open internship roles in Los Angeles in the LA Chamber’s signature tech workforce development program. Our hypothesis suggested that after seeing their skills visualization map, learners would mention a greater number of skills when answering the question, “What would you want a prospective employer to know about you?” The purpose was to test if generating their own skills visualization maps would prompt learners to go into a greater exploration of their skills, knowledge, and abilities and ultimately help them better self-explain.

A control study was undertaken with seventeen job seekers; ten in the experimental and seven in the control. Participants were randomly selected for either the control or experimental group based on when they walked in for their pre-scheduled practice interview at the LA Chamber. Participants for the day were selected by the LA Chamber of commerce as part of their normal workforce placement programming.

Learners in both groups were asked a set of five behaviorally-based questions, as defined by the LA Chamber's standard protocol. These questions are the same as those that would be asked in any given workforce preparation interview at the LA Chamber. For this study, a sixth question was added, which asked participants at the beginning and at the end of the interview the same question: "What would you want an employer to know about you?"

Learners in the control group discussed their resume with the interviewers and those in the experimental were presented with their skills visualization map about halfway through the interview. The first aim was to assess if exposure to a skills visualization map prompted a process of reflection and self-explanation of their skills, as measured by the change in the number of skills mentioned after seeing their skills visualization map; secondly, if exposure to their skills visualization map led to more opportunities for internships, as measured by the number of learners who were recommended for an internship in their subsequent interview.

The interviews were recorded, and the transcripts analyzed as to how many skills a participant used when answering the question What would you want an employer to know about you? for the first and second time. Additionally, the final interview outcomes were tracked for the participants involved in the study to identify if they had successfully been recommended for an internship.

Results

The results showed that when measured against the control group, learners exposed to their skills visualization map were about three times more likely to be recommended by the LA Chamber for an internship (see Figure 2) with one of their partner organizations such as Snap, LinkedIn, Google and Microsoft. Furthermore, approximately 80% of learners used more specific skill language and 250% more skills to self-describe after using their skills visualization map as opposed to those who discussed their resume with a human coach. Interestingly, the words and self-descriptors the learners used were different from what was in their skills visualization map. This suggests that the process of creating a skills visualization map was more effective at encouraging self-reflection and promoting an understanding of one's skills than a traditional resume.

Group	Total participants	Opening statement skills count	Closing statement skills count	Change between opening and closing count	Percentage change	Rec for job?	% recommended for Job
Experimental	11	18	67	**49**	**372.22**	5	45.45454545
Control	6	16	19	**3**	**118.75**	1	16.66666667

Figure 2: Test 2 LA Chamber interviews Results

4. Considerations for further research

This small study indicates opportunities for further research into the efficacy of skills visualization tools to help learners understand and signal how their skills transfer to new and different types of work. However, like with any preliminary study, there are some core assumptions that although founded in the academic research and theory of others require further attention and consideration.

Therefore, the objective of further research is to address the following questions to develop a theory of change about skills and work in the 21st century:

1. What is the signaling gap, and is it due to a lack of self-awareness of how one's skills and experiences can transfer to new and different types of work?
2. Will better-signaling increase access to job opportunities for marginalized and vulnerable youth?
3. What is the most effective mechanism for initiating self-reflection to identify how one's skills, knowledge, and abilities from past experiences apply to new work?
4. Will situated learning experiences help actively solidify the transfer of skills, knowledge, and abilities between old and new work?

It is important to note that special attention must be given to developing an inclusion-first approach to this research. Firstly, because racially and economically marginalized and vulnerable youth are at greatest risk of exclusion in the future and are largely unaware, but also because the intention of this research is to help narrow the digital divide and not to widen it.

As the first step in this direction, the skills visualization tool was created in part because of the barriers of other traditional skills assessment tools that average an 11th-grade reading level and take several hours to complete and interpret. Instead, it leverages existing data about individuals (resume, LinkedIn) and requires no additional time or comprehension on the part of the learner. However, further work needs to be done on testing different data sources that are perhaps more common in marginalized and vulnerable youth. For instance, might information from the

Facebook Application Programming Interface be a more relevant data source, or perhaps letters from school teachers, or class schedules?

5. Conclusion

As we face an uncertain future of work that is dynamically changing at a rapid and unprecedented rate, traditional models of reskilling need a new renaissance. One alternative to this traditional approach is to consider that knowledge, skills, and abilities can be transferred from old work to new work if supported by situative learning practices once in the workforce. Employing skills visualization maps starts to test this idea by seeing if prompting learners to consider how their knowledge, skills, and abilities transfer results in greater access to employment opportunities. Promising preliminary results have laid a strong foundation for further inquiry and expanded research by exploring skills transfer in situative work environments through ethnography and testing.

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