Adaptive Mobile Sensing: Leveraging Machine Learning for Efficient Human Behavior Modeling

(Technical Paper)

Building Organizational Learning Cultures in Response to Technology-driven Workforce Shifts

(STS Paper)

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Introduction

Technology is rapidly transforming all aspects of society: lab generated meat alternatives are altering fast food menus, cars are driving themselves, and high-risk professions, like surgeons, are training through virtual reality. The following proposal will explore how this rapid development in technology will allow unprecedented benefits, but also will require significant changes to avoid serious costs.

Through the Reliable Analytics for Disease Prediction Capstone, a team of eight University of Virginia undergraduates will help to develop reliable disease detection analytics through data collected from wearable sensors (*DARPA WASH ReADI Technical Selection*, 2017). The spread of wearable devices has led to myriad amounts of unstructured data on humans' habits, health, and actions. This data paves insight into advanced health monitoring techniques. However, it is important that these predictions are reliable and actionable. While the mission of the research is to assess warfighter readiness, as the research is funded by the Department of Defense's Defense Advanced Research Project Agency (DARPA), the research and technology developed have wide implications for public health in the future. Paving the way for the future of health monitoring, smartphones will ideally be able to detect possible disease and injury passively using sensors: concussions flagged in real time; cold infections discovered before symptom onset; development of depression detected and treated. Through machine learning and other technologies, the capstone aims to create the foundation for making these societal benefits a reality.

While the rise in technologies, like machine learning and AI, yields many societal benefits, there are also other repercussions. Growth in technological capabilities are creating new superhuman standards of productivity and efficiency in America, but these benefits are coming at the cost of displacing the people who once performed those tasks. Hundreds of millions of people will soon be unemployed unless organizations act to institute cultural changes (Lund, Manyika, & Segel, 2019). Research has shown the best way for today's workforce to keep pace with the speed of growing technological capabilities is if organizations build lifelong learning cultures to foster continual role changes and skill development (Edmondson & Saxberg, 2017). Otherwise, predominantly middle-aged, middle-class Americans will be pushed out of the workforce, as the jobs they dominantly fill will be replaced by machines. The successful creation of learning cultures is critical to fulfill future demanded skillsets, avoid dramatic wage polarization, and reap the full efficiency benefits technology promises. Through analyzing the current and forecasted effects of technology on society's workforce, my proposed research will discover how organizations can adapt through a lifelong learning culture to meet dramatic changes in labor.

Technical Topic (Capstone)

Smartphones and other wearable devices are capable of collecting millions of data about each of its users daily. However, while the potential power of this data in improving society and providing other benefits is unprecedented, there is still much work to be done in creating predictive models that can efficiently extract valuable information from this data. In the Reliable Analytics for Disease Prediction capstone project, unstructured smartphone data will be analyzed in an effort to create predictive health models that assess the health of American troops and their ability to go into battle.

The technical project, advised by Professor Laura Barnes, Medhi Boukhechba, and Lihua (Lee) Cai, is part of ongoing research conducted for the Defense Advanced Research Projects Agency (DARPA) to design and develop reliable disease detection analytics through data collected from smartphones. DARPA is a United States Department of Defense Agency that is responsible for developing innovate technologies for military use (Patel, n.d.). The agency is funding research across several different institutions (University of Virginia, Harvard University, Lockheed Martin, etc.) in efforts to create “ a mobile application that passively assesses a warfighter’s readiness immediately and over time,” (*DARPA WASH ReADI Technical Selection*, 2017). By building predictive health analytics that utilize smartphone sensors, the onset of illnesses, concussions, or even mental health issues can be noticed in real time. Ultimately, smartphone sensors will detect linked disease biomarkers (Figure 1), and these will determine a soldier’s health and their readiness to fight.

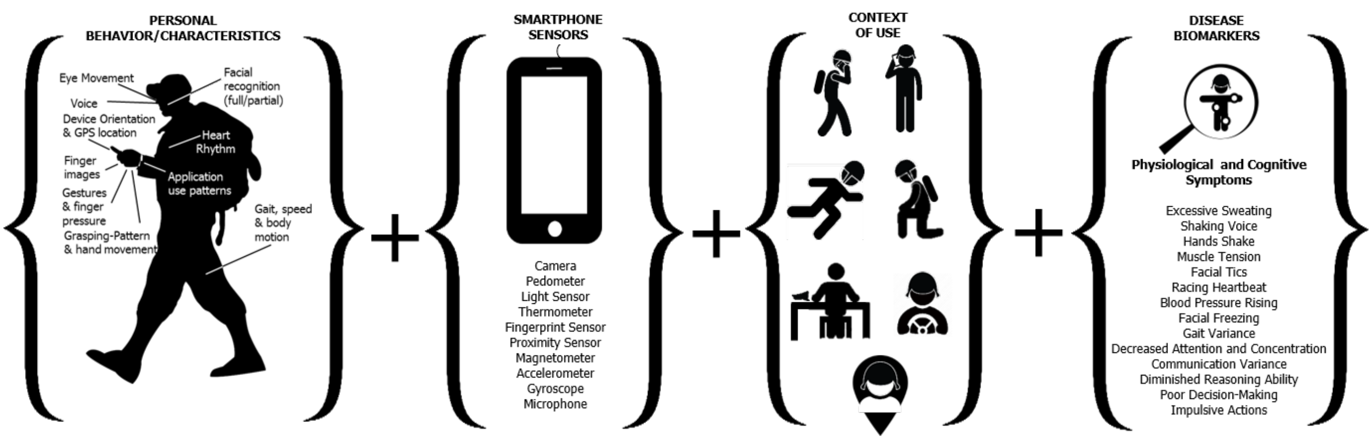

Figure 1. Warfighter Analytics using Smartphones for Health (WASH) health determination. (Patel, n.d.). Smartphone sensors will monitor personal behaviors, such as eye movement, body speed, and voice, within various use contexts and will flag disease biomarkers.

In the current stage of research, the capstone team will develop the tradeoff between data collection frequency and device battery life. The findings are a significant step in determining the feasibility of this technology and in understanding how the user’s environment impacts data collection. By gaining a better sense of these limitations, accurate predictive models can be built without the noise of dead phones or other unwarranted stimuli.

Mobile sensing data used in this research will be collected through the Sensus application. This application, developed at the University of Virginia (UVA), uses "event-driven architecture that triggers actions in response to changes to the device or network state" (*DARPA WASH ReADI Technical Selection*, 2017). Once Sensus is downloaded on participants' mobile devices, the data collected through the application will be utilized to create context recognition models that determine what ambulatory state the user is in, like walking, running, or sitting. This context and personal behavior data will be collected through existing smartphone sensors that are designed to measure altitude, acceleration, Bluetooth encounters, GPS, and much more. Additionally, the Sensus application will push surveys through notifications to participant's mobile phones to create additional context around the data collected. These surveys will ask questions about the user's activities prior to the survey, such as the user's location, length of activity, phone position, and more. This supplementary data will allow the team to build the strong foundational truth that these predictive health models can be tested against for accuracy.

The technical project group consists of nine undergraduate Systems Engineering students. Due of the large size, the team is divided into three sub teams: the Data Modeling Team, the Data Visualization Team, and the Data Collection Team. These teams were constructed for the currents needs of the project, and they are subject to change and overlap depending on the needs in each area. The Data Modeling Team will work to prove the efficacy of adaptive sensing in an attempt to find a balance between data collection and battery usage. Ultimately, this team strives to develop an algorithm as a potential alternative to the adaptive sensing model currently being used. The Data Visualization Team aims to make significant improvements to the web-based visualization platform used by the researchers to increase understanding and context of the data they are collecting. Improvements to this platform will allow better insights to be easily accessible. Lastly, the Data Collection Team is to complete the IRB and design survey questions so that the data collection protocol among the student cohort can begin. Once the IRB is completed and approved, the team will be responsible for organizing the participants in the study. Additionally, other resources used to complete this research includes test phones and desktop computers to run software and view data.

At the end of the study, the team will deliver a recommendation for smart phone data collection that effectively accounts for a user's battery life and critical predictive data and a recommendation for intuitive data visualizations for the researchers' web platform. These recommendations will be published in a conference paper for the May 2020 Systems Information Engineering Design Symposium (SIEDS) and will be utilized to further the DARPA's war fighter readiness research.

STS Topic

The rapid rise of technological capabilities is changing the skills companies need in their workforce. Robotics, machine learning, and AI technologies can not only do human tasks, but they are increasingly able to do these tasks better than a human can (Stiglitz, 2018). About 50% of current work activities today are automatable by current technologies; this rise in technological capability is predicted to displace 400-800 million individuals by 2030 (Manyika, 2017). Automation is rapidly replacing physical activities in predictive environments and data collection and processing the most. Workers in such occupations are expected to be the first affected as organizations continue to adopt this technology. As a consequence, nearly 40% of US jobs are currently in occupations that can be replaced by 2030 (Figure 2), meaning that no community will be immune to these workforce changes (Lund et al., 2019).

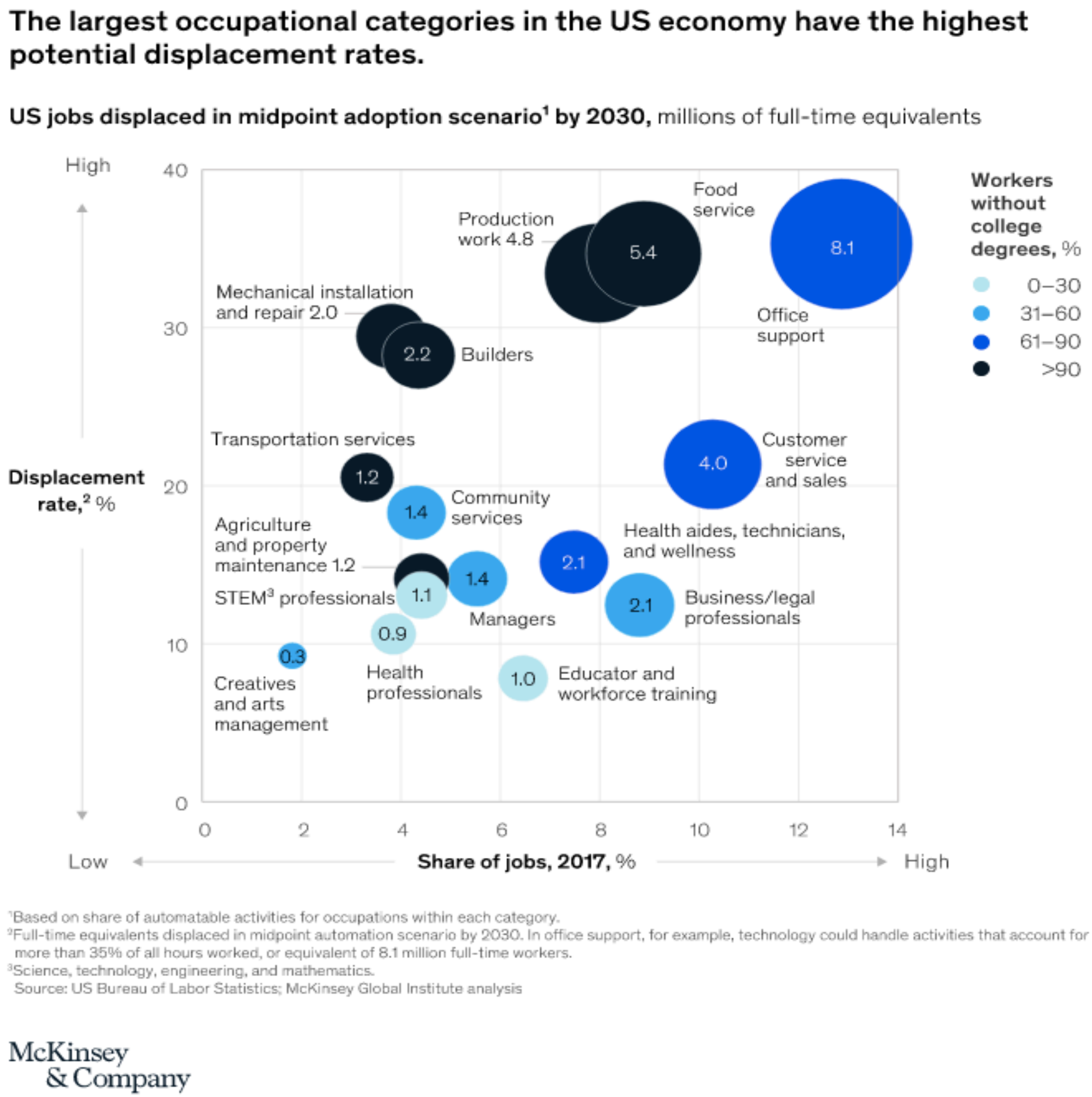

Figure 2. Forecasted US job displacement rate according to share of jobs. (Lund et al., 2019). As shown in the visual, jobs that make up the highest proportion of the US economy are expected to experience the highest displacement rates.

The performance benefits business experience from these automotive technologies, such as quality, speed, and efficiency, are incentivizing further technological growth and business integration. In a survey to major organizations, “64 percent of respondents saw growth ahead in robotics, 80 percent predicted growth in cognitive technologies, and 81 percent predicted growth in AI (Roy, Schwartz, & Volini, 2019).” However, while organizations expect technology to fulfill more tasks, jobs that require socioemotional, problem-solving skills, and critical thinking are projected to rise (Pelster, Haims, & Stempel, 2016). Such skills are considered “human skills” due to their complexity, and so these skills are not currently capable of being replaced by technology (Acemoglu & Restrepo, 2018). As automation increases efficiency and output, the contribution of humans in roles requiring these complex skills rise in importance and value. However, while jobs are developing that require human capabilities, today’s workforce will currently be unable to fill the demand for these skills (Chui, Manyika, & Miremadi, 2016). The increased need for skilled workers is making filling such roles progressively difficult and costly (it takes an average of 42 days to fill an open job today) (Roy, Schwartz, & Volini, 2019b). Furthermore, at the rate technology is evolving, the needed workforce skillsets will continue shifting rapidly; it will be impossible for organizations to fire and hire their way to success in such a restricted labor market (Edmondson & Saxberg, 2017). To meet these workforce shifts, organizations must turn inward, upskilling and reskilling current employees so that these organizations can obtain their required skills, while also alleviating the disproportionate effect automation has on the middle-class, secondary-educated citizen (Manyika, 2017).

To prepare for these effects and to develop the workforce of the future, organizations will have to undergo significant cultural and business shifts. For individuals to feel inspired and empowered to obtain these critical skills, businesses must create cultures of lifelong learning (Pelster et al., 2016). Though, while many researchers agree that a lifelong learning culture is vital to major organizations, significant gaps still remain in the knowledge needed to foster such a culture (Weber, 2019). Hence, the Actor-Network Theory (ANT) will be used as a theoretical lens to analyze the levers needed to create a thriving organizational learning culture. ANT is useful in this discussion, as it stresses the importance of treating human and non-human actants equally (Rodger, Moore, & Newsome, 2009). The use of this theory will explore different combinations of networks that consider both the technological and social aspects of this issue, as to uncover the critical information needed to create organizational learning cultures.

While ANT is useful in this exploration of creating novel cultures to meet workforce needs, critics of ANT exist. Since ANT sets out to follow the actors in any given network, it becomes unclear and subjective which actors should be included and what networks can be "black boxed" (Cressman, 2009). Another shortcoming of this theory is that it also does not "lend itself to dialectical sociotechnical interpretations." These limitations will be accounted for during analysis via the Actor-Network Theory.

Analyzing the levers of organizational learning cultures in response to shifting labor demands in one of the most pressing issues of today. If unmet, the predicted rise in AI and robotic adaption will replace at least 15% of current roles globally, leaving millions of people displaced and unemployed (Manyika, 2017). Given automation disproportionately affects middle-class, secondary-education workers, income polarization within the United States will continue to grow if displaced workers are not reskilled. While rises in technology can spur employment growth enough to offset the job loss, this cannot happen without businesses creating opportunities to boost current workforce skills (Lund et al., 2019). If organizations are slow to transform and displaced workers cannot pick up these needed future skills, global unemployment will rise, and wage growth will dampen (Manyika, 2017).

Research Question and Methods

The research and analysis will aim to answer how organizations can create learning cultures as a response to technological fueled workforce changes. This exploration will consist of documentary research methods, historical case studies, and network analysis.

Through documentary research methods, various reports will contribute to necessary researched needed to create the framework for a successful organizational learning culture. These documents will vary between research reports, publications, and articles that serve to answer the questions: “How is technology changing the skills needed in the workforce,” “What skills do people currently have and how do they attain new ones,” “How can organizations influence their employees to adopt a new culture,” and, most importantly, “What does a learning culture look like?”

Several organizations have structured various versions of learning cultures in the past, so analyzing these historical case studies will provide insight into the history of learning cultures. Microsoft’s employees ‘growth-mindset’ and AT&T’s one-billion-dollar learning transformation will be the two historical case studies analyzed in this report (Caminiti, 2018). Observing what was successful in these studies will support a deeper understanding of what future learning cultures should look like.

Network analysis evaluates the questioned organizations through observed hierarchies, membership, and connections between agents. The technique will achieve a deeper understanding of the social and technical aspects of organizations, employees, and technology, so that the influence each has on each other can be observed. This understanding is vital to building a successful learning culture in response to these technological changes.

Conclusion

In conclusion, this research proposal will deliver actionable recommendations that will benefit society through allowing the full reaping of technological benefits. The capstone project will yield an analysis on the useful smartphone sensors that can find health predictors but account for the battery power needed to run those sensors. At the end of the technical research, a developed breakdown on the tradeoffs between data collection and battery life will be achieved, an important step in making this technology feasible and its benefits attainable to all. On the other hand, the STS thesis will discover the necessary steps organizations must take to support lifelong learning in an era of rapidly changing workforce needs. These findings will both pave the way for society and technology to advance together.

References

Acemoglu, D., & Restrepo, P. (2018). Artificial Intelligence, Automation and Work. *National Bureau of Economic Research*, 43.

Caminiti, S. (2018, March 13). AT&T's $1 billion gambit: Retraining nearly half its workforce for jobs of the future. Retrieved October 2, 2019, from CNBC website: https://www.cnbc.com/2018/03/13/atts-1-billion-gambit-retraining-nearly-half-its-workforce.html

Chui, M., Manyika, J., & Miremadi, M. (2016, July). Where machines could replace humans—And where they can't (yet). Retrieved October 23, 2019, from McKinsey website: https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/where-machines-could-replace-humans-and-where-they-cant-yet

Cressman, D. (2009). Overview of ANT. *ACT Lab/Centre for Policy Research on Science & Technology (CPROST) School of Communication, Simon Fraser University*. Retrieved from https://collab.its.virginia.edu/access/content/group/484deb3f-d8f1-405a-8b1c-5541ca7dd540/Readings/Cressman%20-%20Overview%20of%20ANT.pdf

DARPA WASH ReADI Technical Selection. (2017, June 23). Advanced Technology Labatories.

Edmondson, A., & Saxberg, B. (2017, September). Putting lifelong learning on the CEO agenda. Retrieved October 2, 2019, from McKinsey website: https://www.mckinsey.com/business-functions/organization/our-insights/putting-lifelong-learning-on-the-ceo-agenda

Lund, S., Manyika, J., & Segel, L. H. (2019, July). Future of work in America. Retrieved October 23, 2019, from McKinsey website: https://www.mckinsey.com/featured-insights/future-of-work/the-future-of-work-in-america-people-and-places-today-and-tomorrow

Manyika, J. (2017, December). What the future of work will mean for jobs, skills, and wages: Jobs lost, jobs gained | McKinsey. Retrieved October 21, 2019, from https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages

Patel, T. (n.d.). Warfighter Analytics using Smartphones for Health. Retrieved October 31, 2019, from Defense Advanced Research Project Agency website: https://www.darpa.mil/program/warfighter-analytics-using-smartphones-for-health

Pelster, B., Haims, J., & Stempel, J. (2016, March 1). Fostering a culture of learning. Retrieved October 2, 2019, from Deloitte website: https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2016/fostering-culture-of-learning-for-employees.html

Rodger, K., Moore, S. A., & Newsome, D. (2009). WILDLIFE TOURISM, SCIENCE AND ACTOR NETWORK THEORY. *Annals of Tourism Research*, *36*(4), 645–666. https://doi.org/10.1016/j.annals.2009.06.001

Roy, I., Schwartz, J., & Volini, E. (2019a, April 11). From jobs to superjobs: The impact of AI. Retrieved October 2, 2019, from https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2019/impact-of-ai-turning-jobs-into-superjobs.html

Roy, I., Schwartz, J., & Volini, E. (2019b, April 11). Learning in the flow of life. Retrieved October 2, 2019, from https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2019/reskilling-upskilling-the-future-of-learning-and-development.html

Stiglitz, J. (2018, February 26). *AI, Worker-Replacing Technological Change and Income Distribution*. Retrieved from https://academiccommons.columbia.edu

Weber, L. (2019). Why Companies Are Failing at Reskilling. *The Wall Street Journal*, 13.