

Prospectus

Building Rhythm-aware Technology for Health and Productivity
(Technical Topic)

Are people making decisions based on their own free-will or because of influence from predictive models?
(STS Topic)

By

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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.

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Introduction

An estimated 2.5 quintillion bytes of data is collected every day, which includes, “Every medical procedure, credit application, Facebook post, movie recommendation... is encoded as data and warehoused” (Siegel, 2013, p. 4). Although the process of data collection has remained consistent, the methods and use of collected information have evolved. For the first time in history, large amounts of data can be collected instantly and analyzed due to advancements in computing power. The growing volume and complexity of data has led to significant developments in the field of machine learning and data analytics. Predictive analytics is defined as the extraction of important insights from raw data to make predictions about human behavior (Siegel, 2013, p. 13). The predictive analytics market has experienced tremendous growth and is expected to reach nearly \$11 billion in revenue by 2022, see Figure 1. Organizations have recognized the impact of such powerful technology, and as a result, predictive models are gaining prevalence across various industries. Siegel (2013) claims that “predictive analytics (PA) drives commerce, manufacturing, healthcare, government, and law enforcement” (p. 13). However, as predictive algorithms become more accurate, organizations will also become more successful in generating targeted content. This will ultimately impact human behavior, which will limit our sense of autonomy in decision making.

In addition to understanding the societal implications of predictive models, it is beneficial to explore the mechanics of the technology as well. In the technical project of this research, a predictive model will be developed to enhance human productivity in completing everyday tasks. According to Work Stress Survey (2013), 83% of Americans felt stressed from their job after long hours of work, unrealistic demands and deadlines, and work-life conflict. Companies are constantly seeking new methods to improve the efficiency of their employees by reducing stress.

Reduced productivity can cost billions of dollars in losses. The capstone research team will focus on modeling physiological data with the ultimate goal of providing individualistic recommendations to increase productivity.

The combination of the STS research and the technical project will provide a comprehensive view of predictive modeling. The technical component of this project will focus on developing predictions geared towards enhancing our day-to-productivity, while the STS project will focus on how these recommendations and other similar technologies increasingly bias and train our decisions towards certain actions, hindering our sense of free-will.



Figure 1. Increase in the Revenue of Predictive Analytics Market 2016-2022 (Image Source: Zion Market Research).

Technical Topic

The National Science Foundation sponsored the capstone project known as Building Rhythm-aware Technology for Health and Productivity. The team is composed of seven Systems

Engineering Students working under the faculty advisor Afsaneh Doryab. The goal of the technical project is to enhance human productivity and improve the health and wellbeing of individuals through awareness of personal rhythms. Although environmental factors impact productivity, the human body is independently composed of various biological clocks that may prompt an individual's behavior. The circadian rhythm—a biological process that follows a 24-hour cycle—alternates between a state of alertness and sleepiness in equal intervals and impacts “mental and physical functioning such as our mood, concentration, digestion and sleep-wake pattern” (Abdullah et al., 2015, p. 850). A system will be developed based on data collected from wearable technology to model the internal rhythms. Then, using machine learning techniques, the team will create an algorithm that will make recommendations for specific daily activities based on an individual's biological clock. For example, the algorithm may recommend an individual take a nap at 2:00 PM in order to maximize productivity. The suggested recommendations will be embedded in personal tools and IoT devices.

The initial step in the project is data collection and extraction. The team has found reliable open source Fitbit data that includes sleep, activity, and heart rate from 30 users on GitHub. Data is also being collected from the team members through the use of Oura rings and Empatica E4 wristband to measure their heartrate, skin temperate, sleep activity, and other physiological data. Finally, family members and friends have been recruited to volunteer their data for the use of this project. In addition to the collection of quantitative data, the team members are expected to self-report qualitative data about general emotions, specific activities, and productivity levels. In order to work with human subjects and publish data collected, the team members are being trained through the Collaborative Institutional Training Initiative (CITI) Program for Human Subject Protection Training (IRB).

After data collection, the team must organize the available information into a usable and homologous format. The data must be merged from all the different sources—FitBit, Oura, Empatica—into one dataset. Then, it will be “cleaned” and examined for discrepancies and outliers. The distributions and ranges of all quantitative variables will be inspected and principle components analysis will be applied to reduce the complexity of the dataset.

Once the data is in a workable format, the team will develop a model to identify the most important variables that contribute to the highest productivity based on correlation values. In addition to computation analysis of the data, external research will be done to fully take into account the impact of factors not considered by the variables. The main challenge lies in establishing a specific measure of productivity and making recommendations based on different activities. The team has not fully developed a plan of action for how this will be done, but it will involve a transformation of the qualitative data to a quantitative score of productivity. Once the model is successfully implemented and tested, the team will develop an application or website to illustrate their findings and demonstrate the predictive and recommendation ability of the model.

Since the project mainly involves computational analysis, computers and data analysis programs (Python and RStudio) are the two main resources utilized. In addition, the project has a budget of \$40,000 that can be used to purchase external data or to obtain additional wearable technology with different sensors. Participants will not be compensated monetarily because participation in the study is on a voluntary basis.

Science, Technology, and Society

A general consensus exists that people are morally responsible for the choices they make, intentional or unintentional, and they must be prepared to bear the consequences (Douglas, 2003).

This extends from the idea of free-will and freedom of choice. Although the history of decision making is complex and long, people generally believe that they have the freedom to make decisions regarding career options, living arrangements, schooling, and nutrition (Ayres, 2007). However, it may be insightful to consider the role of technology – specifically predictive models – on influencing human behavior.

Starting from the sixth century BC, philosophers like Lao-tzu and Confucius developed complex principles that became fundamental to the field of decision making. More than 2000 years later, new concepts are still being established as new techniques in technology are incorporated. Buchanan and O’Connell (2006) argue that “thinking machines,” currently known as artificial intelligence, have augmented and improved human decision-making processes. However, Bill Joy (2000) warns that “As society and the problems that face it become more and more complex and machines become more and more intelligent, people will let machines make more of their decisions for them, simply because machine-made decisions will bring better results than man-made ones” (p. 70). Although the debate regarding the superiority of the human brain versus computer power continues to be discussed, nonetheless it is important for humans to uphold their rights to decision making.

The success of the newly developed predictive algorithms indicates that human behavior and decisions are not unique and can be forecasted. For example, 66 percent of all movies streamed and rented on Netflix were selected based on algorithmic recommendations (Ayres, 2007). Educational institutions have developed predictive models to determine admission decisions based on a student’s predicted grade point average. In fact, Georgia State University uses a predicted algorithm to determine the student’s graduation rate based on the grade received from their first course in their major. Out of all the students in the political science major, only 25% of those who

earn a C or below graduate, as opposed to 85% of the students that receive either an A or B. GSU arranges a meeting with an advisor for those students struggling to discuss the option of switching major before wasting money and time (Marcus, 2014). Similarly, financial institutions and commercial banks utilize algorithms to generate a “score” that defines a customer’s creditworthiness (Khandani, Kim, & Lo, 2010). These examples constitute only a small fraction of the uses of predictive analytics in different industries. In most cases, humans are not only dependent on the machine’s recommendations, but the algorithms determine major life decisions involving an individual’s choice of entertainment, education and purchases.

The integration of predictive models can be analyzed through the context of technological determinism. According to Wyatt (2007), the “crucial second part [of technological determinism] is that technological change causes or determines social change.” Human decisions are being altered due to the existence of these algorithms. As a result, human and societal behavior is shifting and conforming to the standard that is set by the very machines humans designed. However, despite the success of predictive models, I argue that their impact is limited by human intuition and psychological behavior. As a result, predictive models can only be contextualized through a *soft determinism* approach. Heilbroner (1967) argues that technology plays a mediating role in sociotechnical systems because its capacity is constrained by human knowledge. As mentioned earlier, the complexity of human behavior indicates that there are many factors that influence decisions. Although predictive models can influence an individual towards a decision, psychological mechanisms internal to the human will always play a role in decision making (Ben & Kim, 2015).

Research Question

I will explore the unattended consequences of predictive analytics on human behavior through my research question: Are people making decisions based on their own free-will or because of influence from predictive models? Based on preliminary research, I identified various user groups that rely upon the use of predictive analytics to make decisions. As a result, I will use comparative case studies to explore the impact of data analytics on four specific fields: education, marketing, entertainment, and politics. My main goal is to analyze how the use of the technology in each field provides evidence using the STS framework of soft determinism. By incorporating cases with different stakeholders and varying predictive models, I can explore the mediating effects of the technology in different contexts.

In addition to case studies, I will collect evidence by conducting interviews with the admissions office at the University of Virginia. I want to determine if (and how) predictive models are used to support admission decisions. If the data gathered from the interview is not sufficient, I will contact other institutions, such as Georgia State University, by phone in the hopes of obtaining similar information. I will analyze the data based on how frequently predictive analytics are utilized and for what purpose. By conducting interviews and exploring case studies, I will have enough evidence to support the soft deterministic approach of sociotechnical systems and to answer the research question.

Conclusion: Timeline and Expected Outcomes

Through the technical project and STS research, I will gain different perspectives of predictive analytics. In my STS research, I will analyze the impact of such powerful technology on societal behavior and take a firm stance on its position between free-will and technological determinism. In the capstone project, I will take the role of the developer and understand the advantages of these algorithms in increasing human productivity.

My team and I anticipate to develop a successful model that will predict and recommend different activities that will optimize human productivity. The capabilities of the model will be shown in a developed website or application. The research will be written in a conference paper and presented at the SIEDS conference. Figures 2 and 3 illustrate the anticipated timetable for the capstone and the STS research accordingly.

Tasks	Timeframe							
	Fall Semester				Spring Semester			
	September	October	November	December	January	February	March	April
Develop understanding of data structure	█							
Data Source Acquisition	█							
IRB Approval		█						
Creation of Data Frame		█						
Data Collection via Subjects			█					
Develop preliminary model			█					
Model Diagnosis					█			
Model Testing						█		
Presentation Development							█	

Figure 2. Timetable of Technical Project (Image Source: Joseph Nelson).

Tasks	Timeframe							
	Fall Semester				Spring Semester			
	September	October	November	December	January	February	March	April
Selection STS Topic	█							
Complete Statement of Topic	█							
Complete Annotated Bibliography		█						
Complete Prospectus		█						
Research Case Studies			█					
Set-up Interview with Admissions Office			█					
Develop Interview Questions					█			
Gather and Analyze Data Collected						█		
Write Final Research Paper							█	

Figure 3. Timetable of STS Research (Image Source: Lina Romeo).

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