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

STS Research Paper
Presented to the Faculty of the
School of Engineering and Applied Science
University of Virginia

By

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May 01, 2020

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 and Motivation

The principles of free-will and determinism have been, and continue to be, topics of interest for psychologists and philosophers. 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 developed due to the intricacy of the topic. Additionally, the development of technological systems intended to aid in decision-making brings forth a new area of discussion regarding the freedom of choice. Precisely speaking, free-will is defined as "the capacity [for an agent] to choose his or her course of action," whereas determinism is "the course of the future is entirely determined by the conjunction of the past" (Timpe, 1995, p. 1). This has been an important subject of discussion mainly because of the desire to understand human behavior. Exploring the distinction between the two philosophies will aid in minimizing the complexity of human decision-making. While arguments continue to be developed for both theories, different psychological approaches outline supporting evidence for each principle.

Humanistic psychologists argue that freedom of choice is possible and necessary for humans to become fully functional. Both Maslow (1943) and Rogers (1951) view self-actualization as a form of motivation for human behavior. Therefore, human actions are motivated by intrinsic desires to reach fulfillment. On the other hand, behavior psychologists, led by B.F. Skinner, argue that free-will is merely an "illusion." Humans learn new ways of behavior from complex interactions and experiences with the environment. As a result, individuals are conditioned to exhibit certain behavior based on the consequences (Cheney & Pierce, 2013, p. 31). Skinner's exploration of determinism can be further expanded by analyzing new developments in technology as a new source of influence on human behavior.

The motivation for this research stems from a desire to explore factors that hinder human beings' sense of free-will. Specifically, new developments in machine learning have proved successful in predicting and influencing human behavior towards certain actions. Additionally, this research seeks to explore not only what actions are being influenced, but also the extend in which technology is predisposing certain behavior. This is an extremely important topic because it explores how a primitive idea, determinism versus free-will, can be analyze as a result of new technology. This study explores the impact of predictive analytics and machine learning on human behavior.

Case Context

An estimated 2.5 quintillion bytes of data is collected every day, which includes, "Every medical procedure, credit application, Facebook post, movie recommendation…[and] 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 experience 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).

In practice, incorporating predictive analytics within establishments has proven to be simple. Edwards (2019) argues that the benefits of integrating machine learning practices within an organization completely outweigh any costs. He claims that it is quite possible for organizations to forecast future outcomes by making use of current and historical data to exploit patterns and trends with the intention of detecting risks and opportunities. This can be done in any field of business, but especially in industries dependent on clients/customers. As a result, businesses are able to make more informed decisions constructed on researched data. The use of predictive analytics has proven to be extremely useful, inexpensive, and successful. However, as predictive algorithms become more accurate, organizations will also become more successful in generating targeted content. This will ultimately impact human behavior, and thus, may limit our sense of autonomy in decision making.

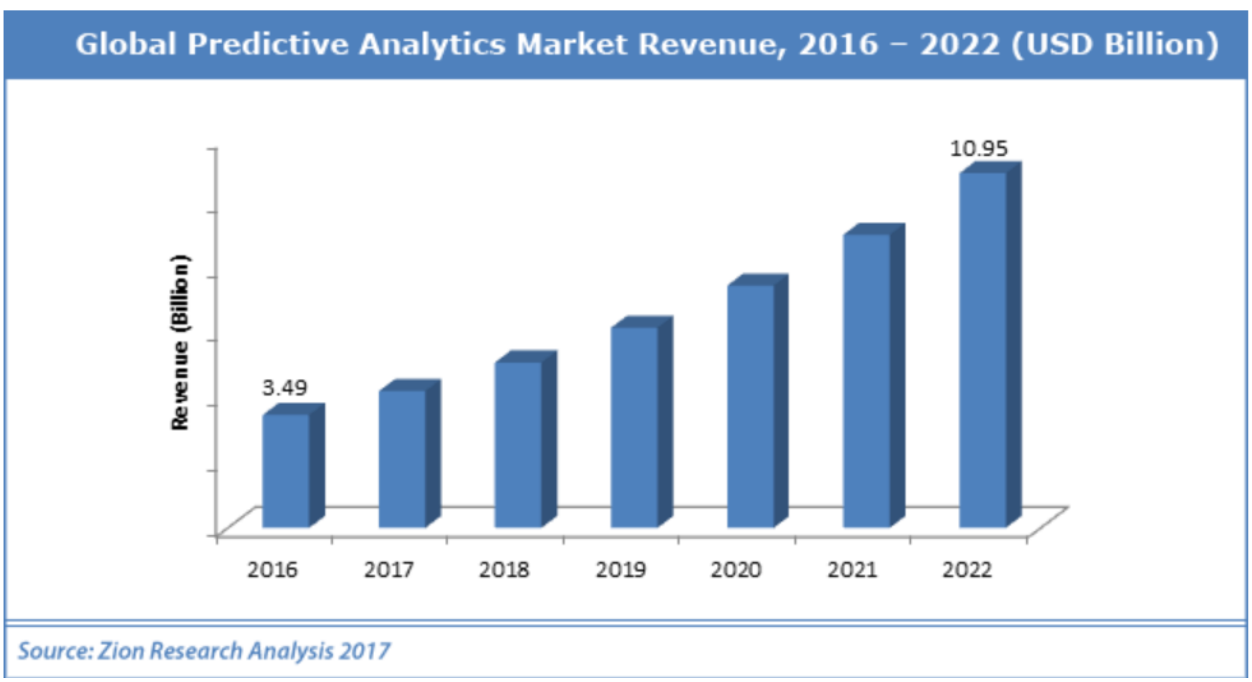

Figure 1. Increase in the Revenue of Predictive Analytics Market 2016-2022 (Image Source: Zion Market Research).

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, as discussed earlier, 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 altering human behavior.

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 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).

Soft determinism is sometimes referred to as “compatibilism” because it serves as a middle-ground between free-will and determinism (McKenna and Coates, 2020). Soft determinism theories outline two causes of behavior: internal and external. Internal causes are voluntary because they are in accordance with a person’s desires, wishes, and personality. While external causes stem from outsides forces. A person may act in a certain manner because they are forced or compelled to act that way due to influences. These actions are not in accordance to a person’s personal desires (McKenna and Coates, 2020). In the case of predictive models, it is clear by the success of the developed predictive algorithms that human behavior and decision are not unique and can be forecasted. However, it is important to analyze when the cause of an action is internal versus external.

Research Question and Methods

I have explored the unintended 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? The question is motivated by the desire to understand how susceptible are human beings to influences from technology. I have used the method of comparative case studies to explore the impact of machine learning in three specific cases: Cambridge Analytica (CA), playlist learning, and Correctional Offender Management Profiling for Alternative Sanctions (COMPAS). I have selected the cases based on their ability to offer different perspectives. For example, the CA case study mainly deals with the ability of machine learning algorithms to influence political ideologies, playlist learning focuses on the k-12 education system and the selection of lessons for students, while COMPAS pertains to law makers and their authority to sentence criminals using the COMPAS software. By incorporating cases with different stakeholders and varying predictive models, I have explored the mediating effects of the technology in different contexts. Additionally, I have utilized a diverse range of secondary data sources that include newspaper articles, scientific journals, magazine blogs, and prior interviews in order to answer my research question. The data collected has been analyzed using the STS framework of Soft Determinism. Particularly, I have evaluated whether the results support the claim that predictive analytics influence human decisions and to what extent.

Results and Evidence

Human behavior can be influenced by algorithms; however, there are limitations to the degree of its impact because of bias and error. Based on three different case studies, it is clear that machine learning is being incorporated in different industries with the intent of improving the decision-making process. The different cases portray people’s varying levels of reliance on machine learning based on the industry, see Table 1 below. For example, the success of political consulting firms indicates that there may be some level of influence on voters to support a certain candidate. In the CA case study, it was shown that with enough data, the company was able to model an individual’s behavior and create personalized advertisements to change their political viewpoints. However, despite these efforts, the top source of influence on political ideology remains to be family relations, which exposes the limitations of machine learning algorithms. In the education and criminal justice case studies, the persons in power—teachers and judges—are dependent on the algorithms to recommend teaching curriculums and jail sentencing on a daily basis. While in both situations the ultimate decisions is made by the teachers and judges, it is apparent that the technology does hold a significant amount of power in influencing the behavior of the individuals making the decisions and the future of those impacted by those decision. While each study poses a different problem, they all incorporate a different aspect of predictive analytics. The main takeaway from the combination of evidence is that algorithms are powerful in influencing behavior, and it is extremely important to analyze the unintended outcomes before completely trusting a machine to make decisions.

Industry	**Study**	**Key Findings**	**Limitations**
Politics	Cambridge Analytica (CA)	Political consulting firms utilize personalized campaigning advertisements to influence voter turnout. CA was hired by the Donald Trump and Ted Cruz campaign, and helped candidate become president.	Research suggests family and teachers as main source of political socialization. CA dependent on individuals sharing strong views publicly
Education	Playlist Learning	Public k-12 school administrators have implemented a new tool to make learning more personalized. Playlist learning selects instructional content for students based on assessment.	Teachers and students have the ability to select different lessons Students with learning disabilities are not representative in the training data
Criminal Justice	Correctional Offender Management Profiling for Alternative Sanctions (COMPAS)	COMPAS software used to predict likelihood of recidivism for offenders. U.S. courts used the score generated to determine sentencing.	Risk scores generates were extremely bias against people of color. Scores generated were often incorrect.

Table 2. Case Studies Comparison Chart.

Politics

Political ideologies have been constructed and shaped by different individuals to categorize and represent certain ideas. Politics are generally personal and based on individual values and morals. However, political views are not innate. Rather, individuals are influenced by several factors, such as family, gender, religion, race and ethnicity, that shape their political attitudes (Feinberg et al., 2017). While all the factors listed are a source of societal connections, a new source of influence, technology, has emerged as a powerful tool. The use of machine learning in political campaigns has gained popularity, especially in the United States. In fact, this market has led to the development of political firms dedicated to technology-based political campaigning. According to data from the Center for Responsive Politics, $552 million were paid to the top 10 political consultants during the 2018 election cycle (Evers-Hillstrom, 2019). This new methodology of campaigning has gained grounds among political parties, due to its effectiveness in influencing voters. In addition to marketing and fundraising, political consulting firms use data analytics to create targeted campaigns (Medvic, 2003).

Cambridge Analytica (CA), a British political consulting firm, was founded in 2013 and declared bankrupt in 2018 due to involvement in the Facebook-Cambridge Analytica data scandal. The company credits itself with Donald Trump's presidential victory by "combining the predictive data analytics, behavioral sciences, and innovative ad tech" (Rathi, 2019, p. 1). Initially, CA was paid over $5.8 million by the Ted Cruz campaign in 2016. While CA's efforts successfully helped Cruz receive the second greatest number of votes, the firm went on to work for the Republican Party's nominee, president Donald Trump (Svitek and Samsel, 2018).

Cambridge Analytica's successful strategy utilized data obtained from surveys and Facebook to generate targeted advertisements. The firm worked with Aleksandr Kogan, a researcher at Cambridge University, to create a survey through Qualtrics, an online survey vendor

(Rathi, 2019). In addition to completing the survey, participants were asked to grant access to their Facebook data, specifically pages they liked and visited through the social media website. However, in addition to the participants data, Kogan was also able to access their friends' liked pages, as long as those friends did not change certain security settings. There were roughly 270,000 participants that took the survey, which granted Kogan and CA access to about 30 million user's data. This strategy of data collection allowed the firm to predict each user's personality based on five key traits: openness, conscientiousness, extraversion, agreeableness, neuroticism, which is often referred to as the Big 5 or OCEAN personality model (Rathi, 2019).

Once the raw data was collected and users categorized, CA was able to create personalized political statements to persuade users to vote in favor of a certain candidate. Christopher Wylie, an ex-employee of CA, exposed the company's manipulative operations, and explains the impact of the firm's actions on users. In an interview with *The Guardian*, Wylie describes the ineffectiveness of previous campaigning efforts to appeal to individuals. Using statements like "I am in favor of jobs in the economy," does not help gain voters because obviously everyone is in favor of a prosperous economy (Hern, 2018, p. 2). However, when people's personality types, specifically their motivations and values, are connected with a political stance, a candidate's message can resonate more effectively. Hern, the interviewer, explains it as "the same blandishment can be dressed up in a different language for different personalities," which in turn can create a connection between the candidate and the voter on an emotional level. Specifically, Wylie explains "If you're talking to a conscientious person" – one who ranks highly on the C part of the Ocean model – "you talk about the opportunity to succeed and the responsibility that a job gives you. If it's an open person, you talk about the opportunity to grow as a person. Talk to a neurotic person, and you emphasize the security that it gives to my family" (Hern, 2018, p. 3). All of these factors can be combined to create personalized advertisements that will appear on a user's social media page. Individuals establish an emotional connection by relating to the messages portrayed, as a result, they associate those sentiments of security, stability and comfort with the candidate. According to Wylie, this technique of personalized marketing is proven to be effective in spreading awareness about a candidate and in turn guarantees votes (Rathi, 2019).

The algorithms developed by CA possess certain limitations. Not only do these companies depend on individuals sharing their political views digitally, but also Wylie explains that most of the people that engaged with the advertisements hold extreme viewpoints about the topics displayed (Rathi, 2019). This indicates that the algorithm is not as successful with individuals that hold moderate beliefs and are not explicit about them.

Education

It is extremely important to prioritize the growth and intellectual development of children in any nation. This begins with schools and classrooms, where children first become exposed to knowledge beyond their understanding. Children begin to ask questions and develop curiosity about unfamiliar subjects. They learn to deal with pressure and problems from teachers and classmates. Above all, education is the most significant determinant of earning potential, which not only influences an individual's health and longevity but also the future of a society (Mshoro, 2020). Therefore, building a strong educational foundation is crucial to ensuring long-term success for nations.

In 2015, the United States allocated $12,330 per full time student enrolled in public elementary and secondary school ("*The Condition of Education 2019,"* 2019). The mission of the Department of Education is to improve the quality of educational programs while assuring equal access to education opportunities by all individuals ("U.S. Department of Education: Mission," 2011). One attempt to improve the k-12 education system has been through the incorporation of technology in classrooms. While the use of these gadgets allows educators to experiment with new methods and provide countless resources to enhance learning, it may also heighten the existing inequality in the education system. Recently, there has been an increased focus on personalized learning. Teachers and administrators recognize the importance in integrating students' strengths and interests into their learning. As an effort to achieve this goal, school districts have implemented "curriculum playlists," which are "educational software programs that rely on [machine learning] algorithms to choose what types of instructional content and learning experiences students have each day in the classroom" (Herold and Schwartz, 2017, p. 1). In Hilliard, Ohio, 600 middle and high school students have been using this new system of learning (Herold, 2014). First, students are prompted to take an assessment to analyze their learning strengths and needs. Then, the software is able to personalize their instructional content based on their learning classification (Herold, 2014). While the initiative is well-intentioned, there are unforeseen consequences when schools rely on machines to make decisions.

The problem with depending on algorithms for educational decisions is the inherent digital bias that exists within these technologies (McKenna, 2019). Machine learning algorithms often reflect the biases of their designers (McKenna, 2019). For example, the computer scientists or programmers may develop algorithms with the assumption that all students in a certain grade have the same amount of knowledge regarding a subject. This is dismissive of the fact that students with disabilities face problems understanding certain concepts that may seem obvious to the average student. Therefore, when models are trained with data from the general population, there is not enough representation of students with special needs (Herold and Schwarts, 2017). As a result, the machine-made decisions counteract the goals of administrators and teachers to provide an inclusive environment of learning for all students. It is disappointing to know that the lessons being taught to our youth are being selected by computers. Sadly, this is not the only place where administrators have relied on algorithms. Machine learning tools are also being used for career and college guidance and teacher evaluations for hiring purposes (Herold and Schwarts, 2017).

The use of playlist curriculum in classrooms can be effective for promoting learning, but it can also hinder the success of students. Teachers and administrators have the ability to change the lessons suggested by the algorithms, but there is certainly a level of reliance on the technology to select the optimal choice of lessons. In general, the playlist curriculum software has only been implemented in a small subset of schools, but it has the potential to spread, especially given the problem with teacher shortages.

Criminal Justice

The criminal justice system in the United States is responsible for investigating, arresting, and prosecuting offenders of the law. According to the 6th amendment in the Bill of Rights, accused individuals are entitled to a fair and speedy trial in criminal prosecutions (U.S. Const. amend. VI). However, studies have shown that racial disparity pervades the U.S. criminal justice system, especially for African Americans and Hispanics (DOJ, 2018). In fact, “African-American adults are 5.9 times as likely to be incarcerated than whites, and Hispanics are 3.1 times as likely” (“Report to the United Nations on Racial Disparities in the U.S. Criminal Justice System,” 2018, p. 1). Clearly, these disparities exist and are prevalent in the justice system. However, rather than attempting to solve these problems, the introduction of crime-prediction technology has intensified the issues.

In 2012, the company Northpointe, Inc. developed and released Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), an assessment software to be used by U.S. courts to predict the likelihood of recidivism for offenders (Park, 2019). COMPAS was used by courts in New York, Wisconsin, California, and Florida's Broward County. The software used an algorithm to create a risk factor for individuals based on the defendant's responses to questionnaires and other unknown factors. The generated score can range from 1 to 4, low-risk, 5 to 7, medium-risk, or 8 to 10, high risk. Prosecutors then used this score to determine a sentence for defendants (Park, 2019).

In 2016, a study done by the nonprofit news organization ProPublica exposed the noticeable bias against black defendants in the COMPAS software (Angwin et al., 2016). Based on the findings from the study, black defendants were more likely than white defendants to be incorrectly judged with a higher risk of recidivism, and white defendants more often received a lower score of risk. Figure 2 illustrates the scores generated for six different offenders based on their crimes. Each row illustrates offenders with similar crimes and historical criminal record. The main takeaway from the figure is that minority individuals often received a higher risk score than the white defendants, despite the similarities in crimes.

U.S. courts relied on this technology as an assessment for criminals for multiple years before the company addressed the issues. The use of this technology only intensifies the problems of racial disparity. This is extremely problematic because it denied certain defendants the right to a fair and objective trial. Not only did the judges' decisions get altered by the existence of COMPAS, but the future of all minority defendants has been negatively transformed. The risk score generated by this algorithm influences every future decision and opportunity available for defendants of color. In this case, the influence of the machine learning algorithm extends beyond the decision-maker because it can cause detrimental damage to the future of innocent men and women.

Figure 2. COMPAS Risk Assessment for Offenders with Similar Crimes (Image Source: ProPublica).

Discussion

This research explored decision-making and human behavior through the STS theory of soft determinism. The results obtained from the different cases have been evaluated to determine if a causal relation exists between human decisions and machine learning technology. Based on the three cases explored, there is strong evidence that humans are being influenced by predictive models to make certain decisions. The success of the newly developed predictive algorithms indicates that human behavior and decisions are not unique and can be forecasted. However, based on the soft determinism theory, free-will does exist and people can choose to make decisions based on their desires, despite influenced from external sources. The evidence obtained reveals that decision-makers are becoming more reliant on algorithms to make decisions, however, the important distinction to note is that they are not forced to use the technology or make the decision recommended. There are limitations that exist within each of the case studies researched that reveal the weakness of predictive algorithms in holding complete control over human-behavior.

The main limitation in attempting to answer this research question is the complexity of human behavior. In general, it is difficult to attribute a specific behavior to one source. Rather it is an accumulation of influences that cause individuals to behave a certain way. Therefore, it is inaccurate to conclude that all behavior is generated from machine learning algorithms and that free-will does not exist at all. Additionally, it is nearly impossible to collect quantitative measurements that attributes a human decision to specified percentage of each source of influence. In an effort to overcome this limitation, I selected case studies in diverse industries in order to determine the impact of machine learning on different stakeholders. However, this limitation will always exist because human behavior and decision-making will remain multifaceted. The second limitation is the immaturity of this technology. Machine learning algorithms are new; therefore, their long-term effects have not been shown yet. This research could be more developed in 10-20 years as more evidence can be collected.

Originally, I planned to conduct interviews with the University of Virginia's admissions office in an attempt to understand the extend in which machine learning systems play a role in admissions decisions. However, after multiple attempts to schedule an interview, they were unable to accommodate my request. UVa's refusal to display transparency by discussing the admission process, even amongst its own students, might be partly explained by the ongoing scandals observed in other higher educational institutions. While it is premature to throw these same accusations towards the university, it is understandable why they may be hesitant to outwardly display the algorithmic biases that may favor students with certain socioeconomic class.

In the future, it would be helpful to conduct different interviews with experts in the field of machine learning, or decision-makers in other industries. This would provide more detailed results regarding the different processes that exist in developing algorithms, and whether a certain behavior can be provoked based on the technology.

As an engineering student, I am fascinated by the immense potential of different technological systems, and I hope to develop different application in the future. This research has allowed me to understand some of the issues that need to be addressed before releasing tools that could determine the course of another individuals' life. The criminal justice case in particular has taught me to be attentive to details when peoples' future is at stake. On another note, this research has provoked me to question my daily decisions and to investigate the true reasons behind my choices.

Conclusion

This research extends beyond one specific tool and its impact on society. Technology is constantly changing as new systems are incorporated into our daily lives. There are unintended consequences when developing powerful tools, and it is extremely important to analyze their impact on human behavior. Next steps in this research includes further analyses of studies in different industries, additional expert opinions and interviews with decision-makers, and the use of a different STS theory for analysis of evidence. Most importantly, the research done in this study is only representative of a small percentage of cases that utilize machine learning. Developers are gaining new insight into more powerful tools that could alter human behavior. The implementation of machine learning has been beneficial for multiple industries not discussed in this research. So, a comparison-based research plan to assess the advantages and disadvantages of utilizing predictive analytics could be useful to understand the benefits and limitations of machine learning technology. However, despite the success of these algorithms, it is our responsibility to maintain our rights to freedom of decision-making. As human beings, we have the ability to control the technology developed rather than allow it to control us.

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