Regulation of AI Industry by Learning From History

Yuan Chen
Madison, USA
chen2243@wisc.edu
https://www.overleaf.com/5621132193kkxrjpmpggjx

INTRODUCTION

The rapid development of Artificial Intelligence has opened a new world of applications that were unimaginable before. From speech-recognizing assistants from service providers, the fully automated world with self-driving cars and smart homes taking care of residents, and even justice systems as a consultant. AI has been gradually taking over many tasks that were initially performed by humans. Many people today interact with AI products in daily life. However, as a decision-making process based on black-box algorithms and invisible data, the wary also grows in users. This lack of trust inevitably negatively impacts user experience and becomes an obstacle when marketing AI products.

Therefore, many Human-Computer-Interaction(HCI) researchers try to find solutions to address the issue, such as building explainable AI to make informed decisions. Another popular approach is using human psychology traits to "trick" users, like virtual agents, to gain trust. While these studies produced some promising progress, they still haven't led to any practical improvement in current AI products. There are a number of gaps that need to be addressed, including but not limited to: 1) Current researches mostly study the interaction between AI and individuals, few of them consider human society as a whole, and study the broader impact of AI on the mass-population. 2) Different users, such as consumers, employees, managers, researchers, and programmers, interact with AI in entirely different ways. The differences need to be considered and researched in well-designed studies. A manager may want to know why the AI makes a business decision. A researcher may wish to tune AI for better results, consumers emphasize convenience, and so on. Current studies overly focus on expert users who have some background in AI systems, while most end-users in the future will be laymen with little knowledge about how AI works or where the data come from. 3) it may be impossible or too costly to make explainable AI if the task is complex. Considering the most explainable algorithm like Decision Tree: it can be clearly explained in a series of logic operations if the decision can be made in a few splits. However, it becomes very taunting when the tree grows bigger, with dozens or hundreds of splits. When it comes to Deep Learning algorithms, even the programmer may not know how to interpret the data and results.

On the other hand, we should realize that even though AI is a relatively young invention, it doesn't mean the problems are new. Researchers have identified several key social issues surrounding AI technology: confidentiality, complexity, unreasonableness, and injustice. Many products with similar characteristics have been invented throughout human history, like aircraft, medicines, and nuclear power, all protected by secrecy and pose a high risk to the public. There are established systems and agencies to regulate the production and distribution of these products. Although they are not entirely trusted by the public, the majority of non-expert consumers have recognized them as trustworthy authorities. In this work, I review research of trust in AI systems and regulatory agencies, compare their similarity, and discuss what we can learn from the history of building trust in our society.

RELATED WORK

This discussion focus on the relationship between the non-expert and regulatory authorities. And do not include other kinds of interactions. The target of this study is to extract information from similar industries. We start with a review of current studies of Human-AI interaction regarding trust. Then, we look at some signature agencies and their relationship with the public. Further analysis about how to use the similarity and past experience to gain public trust will be discussed in later sections.

Trust in AI

Ed Felton identified four social issues of AI: confidentiality, complexity, unreasonableness, and injustice[7]. It's easy to understand that an algorithm, as a product of a company, is a trade secret. Disclosing the exact code and how the algorithm works will not be feasible in most circumstances. For a user or external inspector, it's challenging to know the details about how the decisions are made. On top of that, even if the company shares the algorithm willingly, the complexity of a modern algorithm can make the AI hard to understand. And there is unreasonableness, there are specific facts used by the algorithm and shows clear correlation between the facts and decisions made, but the correlation doesn't align with common sense. Thus nobody accepts

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CHI'20, April 25–30, 2020, Honolulu, HI, USA

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ISBN 978-1-4503-6708-0/20/04...$15.00
DOI: https://doi.org/10.1145/3313831.XXXXXXX

the reasoning behind the decision. At last, injustice has been integrated into many AI systems. Some have biases in training data that infiltrates the decision-making process, and others are outright wrong models generated from incomplete data or human errors. This becomes a severe problem when algorithms are used to influence judges[21] or banks[16].

Not long ago, the European Union passed the General Data Protection Regulation (GDPR) [11] as a comprehensive regulation for collecting, storing and using personal information. As a historical landmark law, it does not only require companies to offer the "right to be forgotten", but also have items to grant "right of explanation" for algorithm-made decisions. The law reflects the prevalent distrust in data and AI technologies. It can be expected that more pressure from the lawmakers and public will demand some level of explanation of the AI decision-making process.

The concern of the "black-box" style of decision-making existed long before the passing of the law. Efforts have been put into the field of so-called Human-Centered AI(HAI), aiming to find a way to enhance the interaction between human and AI systems. Trust is one of the most important aspects of this research.

Despite so many problems related to the explanation of AI systems, it's still one of the most favorable ways to gain trust. Studies on human psychology have provided ample evidence that explanation can increase the level of trust[18]. Leilani H. Gilpin did a detailed analysis on why people need explanation, how to provide it, and the limitation of current explanatory approaches[10]. Keith Darlington summarized many ways to provide explanation in intelligent Systems[5].

Other researchers try to increase trust using human psychological traits. Katharina Weitz and co show that using a virtual agent can increase user trust[23]. Some studies also imply that speaking like an expert may also influence individuals[19].

And there are attempts to fabricate frameworks or guidelines to help design clearly defined and understandable AI design. Andrea Ferrario et al. introduced an incremental model of trust[8]. Saleema Amershi et al. compiled 150 AI design guidelines and proposed an improved 18 entry guidelines[1].

While these methods and models provided some promising progress in terms of gaining trust from users, they are not without limitations. First, most studies focus on expert users and try to explain AI in a technical way, so they are often hard to apply to consumer products[15]. Some explainable AI examples may give incomplete, even false information about the decision-making process due to the algorithm's complexity and mislead the users[17]. Researchers either need to design more sophisticated experiments and involve diversified human subjects. Or we need a new approach to the problems.

Trust in Regulatory Agencies

The explosive growth of the AI sector has visibly changed our lives, but the bureaucratic governments are not agile enough to catch up. After over a decade of privacy concerns on the internet, only one serious government legislation has come into sight. The pass of GDPR is a victory of humans rights against technology exploit, but also marks a failure that the regulation is too slow to follow the changes. We still do not have a comprehensive government-level regulation to ensure the quality and safety of AI products. Only a small portion of the researchers start to put up some effort to fill this gap. Wendell Wallach and Gary Marchant call for agile and comprehensive international governance of AI and robots[22]. Thomas Ferretti urges to prioritize government regulation to solve ethical issues instead of relying on the private sector to self-regulate[9]. Charlotte Stix proposed a few pathways to form actionable principles for policy making[20].

Many mature industries share one or more of the challenges AI is facing today. Medicine, for example, share the confidentiality, complex, and pose a high risk to the public if not properly regulated. The aviation industry is another example, autopilot is very similar to some AI products, and a large part of an airplane is complex and inscrutable. Both industries have some horrendous incidents which result in the establishment of FDA, FAA, and tight regulations. Instead of re-inventing the wheel, what can we learn from existing regulatory agencies and make agile changes to the regulation of AI? Meanwhile, it's also important to learn what leads to the distrust of these agencies and how we can avoid the same pitfall in AI regulations. Some studies regarding the trust of government regulatory agencies are listed below to shine some light on the issue.

Sarh D. Kowitt et al. surveyed awareness and trust in two health agencies, the CDC and FDA[13]. They found high awareness and moderate trust in the agencies and their correlation with age. Lindsey R. Raden et al. sounded an alarm that recent events like Covid-19 have eroded the trust in FDA and reiterated the importance of transparency and the scientific decision-making process[2].

John Downer discussed the relationship between trust and the high-tech industry and the need for expert mediators[6]. Anthony J. Broderick emphasized the importance of government oversight[3]. Timothy J. Logan showed the current error prevention implementations in the aviation industry[14].

So far, some related government agencies have already started investigating the impact of AI in consumer products, such as the Consumer Product Safety Commission (CPSC)[4]. However, no dedicated agency has been organized to oversee AI technology to date.

RESEARCH QUESTION

In this study, I want to explore the following questions:

- What are the identified and unidentified risks of AI systems

- What can we learn from established regulatory agencies to minimize risks and build trustworthy AI products
- What are the pity falls that exist in current regulatory systems that we need to avoid

METHOD AND PROCEDURE

The related work listed in the previous section shows that building explainable AI may be the wrong direction to gain trust from users. In other industries, trust is built on government-level regulation and legislation. Pilots do not report engine status to passengers, nor do doctors explain what a drug does in our bodies. The information provided to the service receiver is a brief description of the outcome, risk, and a statement that a regulatory agency approves the product.

In this study, I will conduct a survey-based study to explore whether people's trust in AI is affected by regulations and the approval process found in other industries. A minor subject is added to investigate how much the education level affects the trust, adoption and concerns about AI technologies. The study contains two major components. In the first half, I will examine the foundation of two regulatory agencies: FDA and FAA, to identify the key elements of the regulation rules and approval processes of high-risk products, as well as the reasoning behind them. I will find the similarities between these industries and AI and formulate a similar protocol for AI products. This protocol and AI products in question are the independent variables in this study. The second half consists of a sample survey with a group of participants. They will provide feedback about their trust in several AI products and how much the existence of the regulatory protocol can shift their trust. The feedback will be the dependent variable. The empirical data will be analyzed to provide insight into my hypothesis: regulation protocols drawn from existing industries can help improve users' trust in an AI product even if the product is not explainable. If the hypothesis is proven, it can redirect the HCI-related AI design to be expertly understandable only, instead of user understandable, making the design process much easier and more feasible.

Formulate Protocol

The AI regulatory protocol will be formulated by finding the answers to the following questions. What are the key elements in the approval process? Why are the elements introduced, and under what circumstances? Are they effective? How are the risks managed? And how to deal with errors when they occur? Then the answers will be compared to the characteristics of AI products and consolidate a group of rules to approve and regulate AI products. Due to the limitation of the study, the protocol will not be a comprehensive list. However, it's not the study's target to find such a protocol but to investigate whether some of these rules can affect people's trust in AI products.

Participants

I recruit participants through the HCI class, family and friends, About 29 data points are collected. Due to the research limitation, these participants may not represent a broad coverage of different backgrounds and are heavily skewed towards individuals with computer science and several with finance background. The education level are all above bachelor degree.

Survey design

The survey consists of three sections. In the first section, the survey will collect the participants' education level as an independent variable. Then the participants are assigned to two groups based on if their birthday is an odd or even number. This question is done to introduce randomness into the sampling of participants. One group will be asked to answer 18 questions under the condition that the AI industry is self-regulated. A table of government regulations is shown to the second group before being asked to answer the same 18 questions.

The question list is made of three topics. The first six are designed to have a baseline about how much participants subjectively trust a specific category of AI products. The AI product in each category is chosen to present different levels of risk, ranging from the least risky one like a music recommendation with slight privacy concern to the life-threatening ones like self-driving cars and medical devices. The next six questions collect the data about how much each participant is willing to adopt an AI on different level, ranging from personal space like personal devices, home to public services, such as schools and government. The last series of questions measure how much the participants' concerns about six aspects of life, from privacy to the full scope of society.

The last two sections of the questionnaire will be compared and analyzed to answer the three questions: 1) how much do the regulations shift the participants' subjective trust in a given AI product; 2) how much do the regulations affect people's willingness to adopt an AI? 3) how do regulations influence the underlying concerns about AI. I aim to use these three questions to demonstrate that the existence of government regulation can enhance consumers' trust in AI products with less concern and be more willing to adopt them.

Analysis

I will analyze the data qualitatively and try to answer two following questions: 1) Can this guideline of policy making change people's trust in AI technologies? If so, are they more willingly to adopt AI products and have less concerns? 2) Does education level make people trust the AI technologies more or less? In this work about 39 data points with 18 answers in each are collected. To answer the first question, the three topics in the survey: trust level, adoption tendency and concerns are compared between the two groups of participants. If a clear improvement appears across the three topics, the guideline is relevant, otherwise it has little impact on people's opinion about AI technologies. For the second question, similar method will be used to show the impact of education level of the participants.

CONSOLIDATING REGULATIONS

The history of FDA regulations

The U.S. Food and Drug Administration (FDA) started from the 1906 Food and Drug Act, which is used to tackle the often tainted food, drink, and drug imports and keep Americans safe. But not until 1927, the Food, Drug and Insecticide Administration become an entity under the USDA and started to oversee the three categories of products mentioned in its name. In later years, due to the change of jurisdiction, the name changed to FDA. The early form of the FDA lacked many regulations we have today, and the market is full of bogus products with questionable ingredients and effects. In the 1930s, a series of incidents caused by poisonous drugs and drinks, such as the infamous radioactive energy drink Radithor and the cure-everything Elixir Sulfanilamide, killed hundreds of people. These tragedies pushed the FDA to overhaul drug and food safety rules dramatically. A few years later, the milestone Food, Drug and Cosmetic Act (FD&C) was passed to replace the old Food and Drug Act. It clearly defines the food, drug, cosmetic products, medical devices, additives and supplements, the premarket approval process, inspection rules, prohibited acts, and penalties. It also requires the manufacturers to provide adequate information about drugs, including purpose and direction of use. Since then, the law has been amended for many times. The most notable one is the 1962 Kefauver-Harris Drug Amendments, which requires drug makers to prove the effectiveness and safety before being submitted to FDA for approval. The Drug Evaluation and Research (CDER) branch were established to take the approval role. CDER is responsible for preventing fraud and providing directions to healthcare professionals with up-to-date guidance. A team of physicians, statisticians, chemists, pharmacologists, and other experts in the related field have to review the data. Only if their independent and unbiased review proves that a drug's health benefits outweigh its known risks, the drug can be approved for sale. The law also requires manufacturers to provide informative documents about the purpose, direction of use, risks, and benefits.

On top of the FD&C Act, the FDA has other tools to regulate the market. In 1941, a batch of contaminated sulfathiazole tablets killed or injured almost 300 people. As a result, the Good Manufacturing Practices (GMPs) are proposed to enforce quality control in manufacturing. GMPs are now a widely adopted standard for a variety of industries. In 1952, the FDA initiated the program of drug reaction reporting in response to the Chloramphenicol incidents, which caused 180 cases of deadly side effects. Several programs were launched later to enhance the reporting process further and store the records, such as the MedWatch and Adverse Event Reporting Systems. Although we still find new problems in drugs every year, the pharmaceutical industry has been significantly safer than a few decades ago, and drug-related death has become a rare sight.

The history of FAA regulations

Similar to FDA, the Federal Aviation Administration started with an Air Commerce Act passed in 1926. The act gave the Secretary of Commerce the power to regulate early aviation activities and enforce air traffic rules. Again, in the 1930s, a series of deadly aircraft crashes killed hundreds of passengers and brought the Civil Aeronautic Act and The Civil Aeronautics Authority (CAA) to the stage. This newly established agency is responsible for air crash investigation and gives the advice to prevent future casualties. In 1956, the mid-air collision between a United Airlines Douglas DC-7 and a Trans World Airlines Super Constellation became the first accident with over 100 fatalities. It reminded everyone about the urgency of aviation safety reform due to the rapidly increasing air traffic and the inadequate air traffic control. Two years later, The Federal Aviation Act was passed, and the Federal Aviation Administration (FAA) was officially created to regulate the safety of the aviation industry and air travel.

The approval process supervised by FAA is extensive and lengthy. The design must go through three-phase of testing: Simulator Test, Airframe Structure Test, and Fly Test. With the recent advancements in computer technology, a flight simulator is an effective and cheap way to test an airplane and train pilots without risking any asset or human life. Therefore, all designs can be tested in a simulated environment and pass basic validation tests before a prototype is built. Once the design is validated in the simulator, it can proceed to the Airframe Structure Test. The mechanical and structural strength is tested in a lab environment in this second phase. The tests include wing loading and deflection, aileron and spoiler functionality during wing loading, fuselage pressure tests, fatigue tests, and flight cycle simulations. The structure has to withstand the condition that mimics thousands of flight cycles. At last, if an airplane passes the first two phases, the manufacture can finally build a complete prototype and fly test it with a pilot. The prototype will fly under normal and extreme conditions, such as high temperature, low temperature, high altitude. All airplane systems are closely monitored during the test, and changes are continuously made to the prototypes to fix new problems. Thousands of fly hours will be needed to simulate the progress from a new plane to a worn one after very long fly cycles. Only after the experts at FAA review the data and believe the airplane is a reliable and safe product, an air-worthy certificate can be issued.

It's not the end of the story once an airplane is on the market. Regulators continue to monitor operations and issues of serving aircraft, and take actions given any arising problem. The most recent example is the ongoing Boeing 737-MAX issue. And if the manufacturer wants to make any change to existing models, they must re-test the airplanes before any of them can be operated in the airspace.

Like the FDA history, this lengthy process results from many disastrous incidents and countless life losses. For example, the fatigue test and tight inspection on high-cycle aircraft resulted from the Aloha Flight 243 incident in 1988, a 19-year-old Boeing 737 that almost disintegrated mid-air. However, due to the ever-evolving regulations, an airplane has become the safest traveling method, with only one fatal accident in 107 flight hours, significantly less than cars and other transportation alternatives.

Proposed Regulations

As previously mentioned in the FDA and FAA history, the current regulations are built upon hundreds of fatal incidents and countless loss of lives. It's crucial not to repeat the same process and learn from the past. It's especially true since AI technology is developing faster than the drug industry and aviation industry. It requires close observation and swift reaction to potential risk. This section compiles some key components in the FDA and FAA regulations and proposes a guideline with five categories and nineteen items. The guideline is shown in Table 1.

Table 1. Guideline for Government Regulation over AI Industry

REGULATION CATEGORY	CONTENT
LABEL	purpose and function of the AI
	Limitation of the AI
	Error rate and potential risk of the AI
	Certificates and the organizations which issue the certificates
PRIVACY	Users have the right to know what data is collected
	Users have the right to who the data is shared with and what data are shared
	Users must be provided with a way to opt-out the data collection and sharing
APPROVAL	Companies must prove the safety and effectiveness of an AI product scientifically and provide related data for review
	A group of experts from related fields in the overseeing administration must review the data and independently evaluate the product.
TESTS FOR EFFECTIVENESS, SAFETY, AND USABILITY BEFORE APPROVAL	Simulated test in virtual environments
	Lab tests of hardware and software
	Field tests in real-world environments
	Fatigue test for long-time and many-cycle uses of the AI product
	Test against different groups of the population, such as race, age, gender.
ONGOING MONITOR & RISK MANAGEMENT	AI providers have the responsibility of identifying and mitigating risk even after the product is approved for sale
	AI system must show a warning when an error occurs
	AI providers must provide a practical emergency checklist to reduce immediate danger to the user
	AI providers must maintain the safety, effectiveness, and privacy of their products and recall defective systems
	The government provides a channel for problem reporting and will take action to remove any AI product from the market if a company fails to follow the regulations

RESULT

Effect of Government Regulation

Overall, the guideline of government regulation policy has a significant impact on the three topics. The most substantial changes are shown in the subjective trust level (Figure 1). If government regulation exists instead of self-regulating, the average trust in AI products increases from 2.4 (slight distrust) to 3.2 (somewhat above neutral). As expected, AI product with minor risk is the most trusted across the scope. However, the life-threatening self-driving car and medical diagnose tools are also trusted than the work evaluation and personal assistant devices. It's possible that people unconsciously think the companies will test these dangerous products more before releasing them to the market. At the same time, the performance of a work evaluation software can be very subjective and can ruin a person's life. This difference may be worth further investigation in the future. The self-driving car also exhibits the highest increase of trust if government regulation exists with a boost from 2.5 to 3.6, a level that is the same as the music recommendation app.

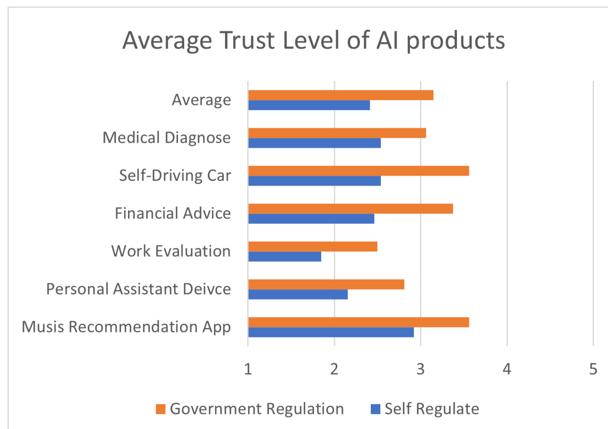

Figure 1. Average trust level of AI products

In the meantime, the data show a smaller change in the willingness of adoption (Figure 2), with a change from 3.3 to 3.5. Personal device is the only outlier that displays a minor decrease from 3.5 to 3.4. This could reflect that the participants feel neutral about using AI technologies in their personal devices no matter what. All other categories exhibit a moderate increase in willingness. Corresponding with the low trust in personal assistant devices like Echo in the trust survey, participants are most reluctant to adopt AI products at home. And school is the place they want AI technologies the most.

Regarding the concerns about AI technologies (Figure 3), the government regulation decreases concern levels in every category from an average of 3.5 to 3.0. Participants, in general much less concerned about injustice and discrimination. And not surprisingly, job security changes very little in this survey since no policy is mentioned in the guideline can effectively counter it. Privacy is still the top concern about AI, even after decreasing from 4.2 (very concerned) to 3.6 (somewhat concerned). Privacy is the concern that draws the most attention, and long-term social impact is the least concerned about.

The results show a clear improvement over trust if government

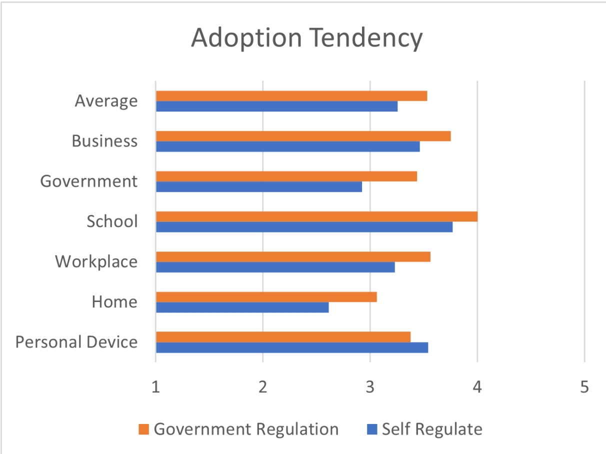

Figure 2. Average Adoption tendency

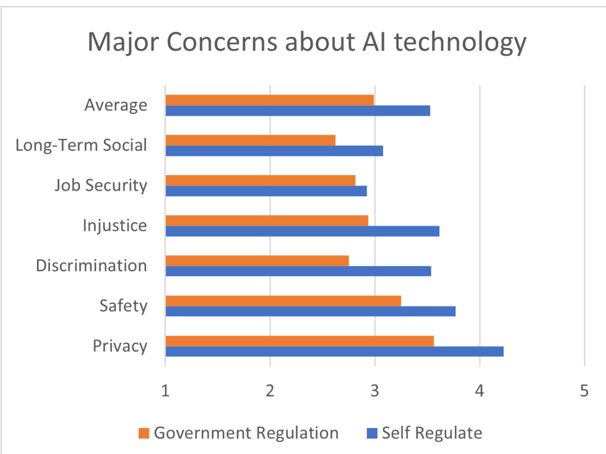

Figure 3. Major concerns about AI technology

regulation exists. And also demonstrate a vague pattern about the three topics. Suppose an AI technology is closer to personal life and the participant uphold little control over it. In that case, it's less likely to be trusted and adopted, i.e., assistant devices at home, work performance evaluation. On the other hand, if an AI product is further away from personal life or can be easily controlled, it can be trusted more and easier to adopt, like in the public service sector or a car. Participants are also more concerned about issues close to themselves, like privacy or safety, and less concerned about discrimination or social impact, which is not an immediate threat.

Effect of Education Level

The education level influences the three topics in an interesting way (Figure 4, 5 and 6). Participants with Ph.D. degrees have significantly lower trust in AI technologies, are moderately less willing to adopt AI, and show more concern than the participants with Bachelor's or Master's degrees. This finding echos the result from a recent study [12] about COVID-19 hesitancy across different education levels, which shows the population with Ph.D. degree exhibits the highest hesitancy and slowest decline of hesitancy. And the population with a Master's degree shows the highest trust and lowest hesitancy in this study and Wendy's work. Further works are needed to explain the phenomenon. A possible explanation is that the group with lower education levels do not have the training to understand statistical data but will be persuaded by the government and experts over time. However, Ph.D. degree holders are trained to be skeptical. Solid evidence is needed to move the opinion of this group.

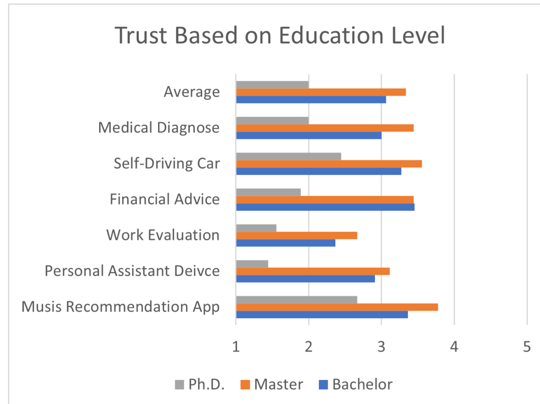

Figure 4. Trust based on education level

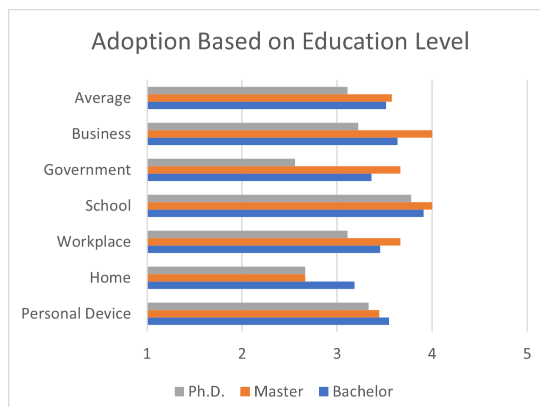

Figure 5. Major concerns about AI technology

Overall the participants with PhD degree has the lowest average trust in AI technology with a score of 2 (somewhat distrust) and neutral about adoption and highest concern. And participants with Master's degree has the highest trust in AI with a score of 3.3 and highest tendency to adopt as well. Participants with bachelor degree are the least concerned about AI technology.

Next, I examined the correlation between the 18 scales with policy and education level. The correlations are listed in Table 2. The correlation values echo the results from the descriptive analysis above. Adoption of personal devices and concern above job security is not correlated with regulation

Table 2. Correlation between IVs and DVs

	POLICY EXIST	EDUCATION LEVEL
TRUST_MUSIS_ RECOMMENDATION	0.259	-0.219
TRUST_ECHO	0.275	-0.488
TRUST_WORK_EVAL	0.316	-0.307
TRUST_FINANCE	0.324	-0.448
TRUST_CAR	0.358	-0.228
TRUST_MEDICAL	0.221	-0.331
ADOPTION_PERSONAL	-0.095	-0.103
ADOPTION_HOME	0.201	-0.199
ADOPTION_WORKPLACE	0.178	-0.142
ADOPTION_SCHOOL	0.102	-0.045
ADOPTION_GOVERNMENT	0.234	-0.289
ADOPTION_BUSINESS	0.135	-0.147
CONCERN_PRIVACY	-0.355	-0.057
CONCERN_SAFETY	-0.222	0.106
CONCERN_DISCRIMINATION	-0.331	0.218
CONCERN_INJUSTICE	-0.335	0.227
CONCERN_JOB	-0.039	0.140
CONCERN_LONG_ TERM_SOCIAL	-0.246	0.258

Table 3. One way ANOVA against policy

	F VALUE	P VALUE
TRUST_MUSIS_ RECOMMENDATION	1.938	0.175
TRUST_ECHO	2.203	0.149
TRUST_WORK_EVAL	2.99	0.0952
TRUST_FINANCE	3.17	0.0863
TRUST_CAR	3.969	0.0566
TRUST_MEDICAL	1.393	0.248
ADOPTION_PERSONAL	0.247	0.623
ADOPTION_HOME	1.138	0.295
ADOPTION_WORKPLACE	0.879	0.357
ADOPTION_SCHOOL	0.284	0.598
ADOPTION_GOVERNMENT	1.56	0.222
ADOPTION_BUSINESS	0.5	0.486
CONCERN_PRIVACY	3.888	0.059
CONCERN_SAFETY	1.399	0.247
CONCERN_DISCRIMINATION	3.323	0.0794
CONCERN_INJUSTICE	3.421	0.0754
CONCERN_JOB	0.041	0.841
CONCERN_LONG_ TERM_SOCIAL	1.744	0.198

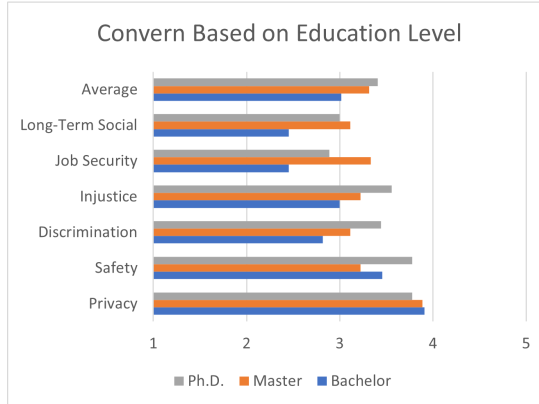

Figure 6. Major concerns about AI technology

policy. Trust of the AI products is moderately positively correlated, while the rest of the concerns are moderately negatively correlated. And the willingness to adopt is weakly correlated to regulation policy. On the other hand, education level has an almost reversed impact on the scales. Trust level and willingness of adoption are lower while education level is higher, and vice versa. In the meantime, concern level is positively correlated with increased education level. However, the inferential statistics analysis indicates that the results are insignificant. The F-Values and P-Values regarding the two IVs are reported in Tables 3 and 4. As shown in Table 3, even though a couple of scales are close to the threshold of 0.05, such as trust in self-driving cars or concern about privacy, non of the scales is significant. Therefore the data is not enough to reject the null hypothesis. A few scales in Table 4 are significant, such as trust in personal assistant devices and fiance advisory algorithms. The high P-Values imply an overall not significant relationship.

CONCLUSION

In this study, I formulated a guideline of government regulation for the AI industry. And then designed a questionnaire to explore whether a government regulation policy under the guideline can increase the participants' trust in AI products, thus are more willing to adopt the technologies and reduce the level of concerns. The preliminary examination of the data shows encouraging results, in which trust and willingness of adoption increase across the board while the concerns are alleviated. However, further analysis of the data tells a different story and shows most of the scales used in this study are not significant enough to prove the alternative hypothesis. There could be several reasons that led to the result. Either the guideline is not very practical, or government regulations are not well trusted by the participants, or not enough data points.

Table 4. One way between participants ANOVA agianst Education Level

	F VALUE	P VALUE
TRUST_MUSIS_ RECOMMENDATION	1.355	0.255
TRUST_ECHO	8.438	0.00725
TRUST_WORK_EVAL	2.808	0.105
TRUST_FINANCE	6.779	0.0148
TRUST_CAR	1.484	0.234
TRUST_MEDICAL	3.321	0.0795
ADOPTION_PERSONAL	0.287	0.596
ADOPTION_HOME	1.111	0.301
ADOPTION_WORKPLACE	0.558	0.462
ADOPTION_SCHOOL	0.054	0.818
ADOPTION_GOVERNMENT	2.455	0.129
ADOPTION_BUSINESS	0.598	0.446
CONCERN_PRIVACY	0.087	0.77
CONCERN_SAFETY	0.308	0.583
CONCERN_DISCRIMINATION	1.352	0.255
CONCERN_INJUSTICE	1.47	0.236
CONCERN_JOB	0.539	0.469
CONCERN_LONG_ TERM_SOCIAL	1.93	0.176

Further work is needed to gain a more clear picture of this issue.

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