Higher Education and the Automation of Inequality through "Inattentional Blindness" : Survey Study

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ABSTRACT

The accelerating incorporation and reliance on Artificial Intelligence (AI) and Data-Driven algorithms that assist us in sensitive domains such as education, social services, and the criminal justice system, have provided technology systems the power to automate inequality through algorithmic discrimination. Recent research has identified the narrow technical approaches technologists often take to solve social problems (known as "*inattentional blindness*") as one of the main contributors to algorithmic bias and discrimination in AI systems. However, there is little research examining the materialization of this phenomenon in higher education. As such, we conducted a quantitative survey study among California State University Dominguez Hills (CSUDH) students in the *Computer Science/Technology* related fields, to investigate if this phenomenon is also observed among university students. Our investigation employed a survey questionnaire designed to quantify the "level of significance" participants attributed to statements from two distinct categories, one associated with important *Social & Ethical* real-world considerations of technology systems and the other one associated with *Technical & Economic* ones. Results demonstrated that students in the Computer Science/Technology fields attribute a greater overall significance to *Technical & Economic* considerations in comparison with important *Social & Ethical* ones. A compelling indication that "*inattentional blindness*" might also be a considerably persistent pattern among university students.

I. Introduction

As coined by some researchers, "*inattentional blindness"* [13] refers to the phenomenon of algorithmic biases that emerge when the system developers fail to capture the desired complex real-world goals in their target variables and problem specifications procedures [16]. A direct result of the single-discipline and mostly centered university curriculums of the technology-related fields. Technologists are not necessarily trained to identify social and cultural considerations of their developments, which causes them to take narrow technical approaches to deal with social problems [6].

The main objective of our study was to investigate if this pattern of "inattentional blindness" currently aggravating the technology industry [13], is also observed among university students of a public and federally designated Hispanic Serving Institution (HSI) such as CSUDH, or do the respective intersectional identities of a more diversified student body have a detectable effect on the level of significance students attribute to social and ethical implications regarding algorithmic bias in technology.

To conduct our investigation, we adopted a quantitative methodology through an online survey questionnaire designed to assess the perceptions of undergraduate and graduate students in the *Computer Science/Technology* fields, on various real-world technical, economic, social, and ethical implications of technology systems.

The adopted survey design utilized statement rankings to calculate *cumulative scores* as a measure of the "level of significance" participants attributed to statements from two different *Statement Categories*. One associated with *Social & Ethical* considerations, and the other one is associated with *Technical & Economic* ones.

These *cumulative scores* were then empirically assessed, first through a parametric pilot Factorial Repeated Measures Analysis of Variance (ANOVA) and then by additional non-parametric statistical tests: a Friedman's ANOVA test followed by different Wilcoxon Signed-Rank and Man-Whitney tests, to determine the significant cause and effect relationships between the different *Statement Categories*, *demographic* and the *cumulative scores* variables obtained.

II. Literature Review

Data-driven AI algorithms used in systems that assist governments, courts, public services, bureaucratic processes, hospitals, schools, public service delivery, etc., have the power to reproduce biases and inequalities found in the historical data of the societies they are 'trained' on [10, 23]. Thus, algorithms can be biased, violent [11], have the power to discriminate [2], dehumanize [19], and can facilitate government oppression of vulnerable populations and minorities [3]. As a result, organizations such as the Algorithmic Justice League (AJL) and American Civil Liberties Union (ACLU), in addition to various critical researchers have documented and disclosed how these systems perpetuate racism, sexism, ableism, and other harmful forms of discrimination [0]. Their efforts highlight the particularly difficult challenge of combating injustice in the form of harmless computer system decisions.

Recent studies focused on the identification of sources of algorithmic bias, suggest that two of the most significant factors contributing to the development of these socially insensitive systems are: (i)The limited understanding by AI engineers, developers, and researchers, of social science subjects such as gender, race, class, criminality, intersectionality etc., and how they relate to of algorithmic bias [25]. And (ii) the need for diversity in the technology industry [14, 24].

The training and education of AI engineers, developers, researchers, and those involved in the development and study of data-driven innovation systems, is quite centered and mostly based on a single discipline such as computer science [13]. Social and ethical subjects are often given lower priority than technical ones. University curriculums of these technical fields rarely demand the profound interdisciplinary thinking necessary for system developers to associate their technological developments with plausible ethical consequences in socially and culturally sensitive domains [4, 17].

While recent findings have identified various sources of algorithmic bias, there is limited research examining how these factors materialize in institutions of higher education. Therefore, this study aimed to explore these considerations and investigate if this pattern of "inattentional blindness" is also persistent amongst CSUDH's diversified student body.

Considering all the factors described above, we hypothesized that while this phenomenon might also be persistent among CSUDH students in the Computer Science/Technology related fields, students with marginalized identities might be more aware of bias, discrimination, and other ethical implications in the context of technology and AI algorithms.

III. Methods

This study employed a descriptive-analytical method and relied on a quantitative survey to collect demographic and ordinal data. The study questionnaire was validated and approved by the CSUDH Institutional Review Board (IRB). The survey was distributed among students through RQ codes, flyers, email, and social platforms such as Discord. And it remained open from April 2022 to September 2022.

Population and Sample

Our study population included a total of 360 undergraduate and graduate students, 18 years old or older, who were enrolled at CSUDH during the Spring 2022 semester and were pursuing a major, minor, or graduate degree in one of the following fields: *Computer science*, *Computer Technology*, *Cyber Security*, or *Information Technology*. Subjects were identified and recruited using snowball sampling methods. A total of 104 student survey responses were collected. However, due to the adopted survey design, the actual study sample consisted of $N = 65$ subjects. The ages of participants ranged from 18 to 35 years ($M = 24.41$, $SD = 3.99$). Calculations indicated that a sample of $N = 65$ would provide a 90% confidence level and a 5% margin error of detecting correlations.

The demographic data of our study subjects is summarized by Table 1.

Table 1.	Subject Characteristics	
Demographic Categories		Category %
Class Standing Categories	First Year	4.3%
	Sphomore	10.1%
	Junior	21.7%
	Senior	50.7%
	Graduate Student	13.0%
Race & Ethnicity Categories	Hispanic/Latino	49.3%
	Asian	30.4%
	White	5.8%
	Native American	0.0%
	African American	2.9%
	Middle Eastern	2.9%
	Mixed Race	7.2%
	Other	1.4%
Gender Categories	Male	81.2%
	Female	18.8%
Major & Graduate Degree Categories	Computer Science	81.2%
	Information Technology	8.7%
	Computer Technology	8.7%
	Cyber Security	1.4%

Questionnaire Design

The structure of the survey questionnaire in its final form was divided into two main parts. The first part consisted of 14 demographic questions that captured, *class standing*, *major*, *race & ethnicity*, *gender identity*, *age*, *annual income*, and *parental level of education attained*, to validate the subject's eligibility for participation.

The second part consisted of 10 *Question Topics* related to issues and contributions of *Targeted Algorithms*, *Social Media*, *Artificial Intelligence*, and recent controversial issues related to *Google*, *Facebook*, and *Amazon*, to collect ordinal data in the form of *statement rankings.*

These 10 questions were formulated based on current real-world articles, blogs, studies, and academic papers that have investigated or discussed the mentioned topics. For each question, students were presented with a *Topic* and six related statements from two different *Statement Categories:* (i) *Social and Ethical* aspects of technology associated with human-technology interactions and (ii)*Technical and Economic* aspects of technology factors.

Participants were then asked to rank the six given statements in order of significance, by assigning the statement they considered "most significant" the number 1 ranking and the statement they considered the "least significant" the last number ranking.

An example of the structure of our questionnaire questions and related statements is shown in Figure 1. It should be noted that in the actual survey completed by participants, statements were presented in a random order and the questions did not indicate any association between the given statements and their corresponding categories.

Figure 1. Survey Question Sample

Q. Rank the following six important possible Future contributions of ***Artificial Intelligence*** in order of significance:

Category 1: Social and Ethical **Effects of Technology**	Category 2: **Economic and Technical Factors**
AI's potential to increase accessibility and inclusivity for individuals with disabilities by assisting daily living	AI's potential to predict with greater accuracy economic crises
AI's potential to help solve current humanitarian crises such as homelessness and extreme poverty.	AI's promising extraordinary advances in physics, mathematics, engineering, and space exploration
AI potential to be a tool for promoting social justice and equality.	AI's advances in robotics have the potential to significantly reduce the cost of labor

IV. Data Analysis

Data was collected, categorized, and coded using the Alchemer survey platform and then analyzed using the IBM Statistical Package for the Social Sciences (SPSS) software.

Based on the assigned *statement rankings*, we calculated the *cumulative scores* each participant assigned to *Category 1 statements* and *Category 2 statements*. These cumulative scores were calculated utilizing a Likert-based point scoring method in which a ranking of "1" was attributed zero points, a ranking of "2", one point, and so forth.

Two different point scales were used throughout the 10 *Question Topics*: *Point Scale* 1 and *Point Scale* 2, 4-point and 6-point based scales, respectively. Cumulative *Category 1* and *Category 2* scores were calculated for each of the *Point Scales* separately and then combined as overall scores. We used these *cumulative scores* to quantify our measurement of the degree of significance/importance each participant attributed to matters/topics addressed in *Category 1* in comparison to those in *Category 2*. In this adopted scoring system, a lower *cumulative score* indicated that the participant assigned higher ranks (1 to 3) to statements from the specified category. The collected *cumulative scores* are described by the following table.

Cumulative Scores By Category Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation
Category1 4P_Scale	65	11.00	3.00	14.00	8.1538	2.67062
Category2 4P_Scale	65	11.00	4.00	15.00	9.8462	2.67062
Category1 6P_Scale	65	49.00	26.00	75.00	49.3231	10.51949
Category2 6P_Scale	65	49.00	30.00	79.00	55.4000	10.39351
Category 1	65	56.00	33.00	89.00	57.4769	11.77804
Category 2	65	56.00	34.00	90.00	65.2462	11.63780
Valid N (listwise)	65					

Preliminary Analysis:

After *cumulative scores* were determined, we computed the descriptive statistics such as the mean, standard deviation, frequencies, and percentages of our *demographic* and *cumulative scores* variables.

To account for the added values and variability that result from combining Likert scales into indexes, we conducted preliminary tests to check that the assumptions of parametric data such as normal distribution and homogeneity of variance, were met.

- Results of the K-S test of normality indicated that overall *cumulative scores* for the two different *Statement Categories* and two different *Point Scales* had a normal distribution $D(65) = .10 \pm .05, p > .05$. However, the individual *cumulative scores* for 10 *Question Topics* did not share this normal distribution. Therefore, the analysis of our data involves parametric statistics only as a pilot analysis and then applies non-parametric procedures that take into account the ordinal nature of the collected data.

- The null hypothesis of random ranking behavior for each question was tested using Kendall's tau correlation coefficient. The null hypothesis was rejected for 60% of the questions, while the other 40% were near a significant value of $p < .05$, indicating some consistency among participants' statement rankings.

Pilot Statistical Analysis

The first step of our data analysis consisted of a pilot Factorial Repeated Measures Analysis of Variance (ANOVA) that evaluated how the *Statement Categories*, and their interaction with the *Point Scale* used, affected the calculated *cumulative scores*.

This pilot evaluation analysis compared two independent variables: *Statement Category* and *Point Scale* used. Each variable contained two levels that completely crossed over to produce four experimental conditions: *Category1_PointScale1*, *Category1_PointScale2*, *Category2_PointScale1*, *Category2_PointScale2*.

The results of our pilot analysis reported three effects: the main effect from *Statement Category* and *Point Scale* used and the interaction effect between these two variables. All effects were reported significant at $p < .05$ and are summarized as follows:

- The *Statement Category* to which statements belonged to, had a significant main effect on the calculated *cumulative scores* $F(1{,}64) = 7.18$, however contrasts did yield a medium size effect $r = 0.31$, which indicated limited practical applications.
- Statements that belonged to *Category 1* had a lower mean score of 28.74 (SD $= .730$), in comparison with statements from *Category 2* with a mean of 32.62(SD = .730).
- There was also a significant main effect observed from the *Point Scale* used, indicating that scores from *Point Scale 1* were much higher than those from *Point Scale 2*. This was an expected result, and its effect was not meaningful to our analysis since our focus was to assess the effect of the *Statement Categories* and their interaction with the *Point Scale* used.
- There was not a significant interaction effect found between the *Statement Category* and the *Point Scale* used.

Non-Parametric Analysis:

Considering the violation of the normal distribution by the *cumulative scores* of the *10 Question Topics*, we followed our pilot analysis with additional non-parametric statistical tests: Friedman's ANOVA and different Wilcoxon Signed-Rank and Man-Whitney tests.

First, for each of the two *Point Scales*, we conducted a Friedman's ANOVA test to evaluate differences between *Category* 1 and *Category* 2 scores.

- Results indicated that cumulative *Category 1* and *Category 2* scores for the *Point Scale 1* questions significantly differed. $x^2(5) = 17.6, p < .05$. Similarly, results for the cumulative *Category 1* and *Category 2* scores for *Point Scale 2* questions also were significantly different $x^2(13) = 30.6, p < .05$

We then followed up on these findings by conducting Wilcoxon Signed-Ranked and Man-Whitney tests:

A Wilcoxon signed -Ranked test was conducted to compare the overall *Category 1* and *Category 2 cumulative scores* as two related conditions.

- Results of the test indicated that for our sample population, cumulative scores of statements belonging to *Category 2* were significantly higher ($Mdn = 67$) than those from *Category1* ($Mdn = 56$), $z = -2.711$, $p < .05$, $r = -0.4$. In accordance with the adopted scoring method, the lower *Category 1* scores indicate that statements related to *Technical and Economic Technological factors* were considered more significant (received higher rankings) by participants, in comparison to statements related to *Sociological and Ethical Effects of Technology factors.*

Consecutively, various Man-Whitney tests were conducted to further assess how *Category 1* and *Category 2* cumulative scores varied between the different demographic groups. Participants were classified into different groups using the *demographic* variables collected during the first portion of the survey questionnaire such as: *Class_Standing, Gender, Race_Ethinicity, Major, Annual_Income, Age, Parent_Educational_level, LGBTQIA+_membership, Disability, etc.*

Separate Mann-Whitney tests were conducted with each of the different demographic grouping variables as the independent variable and the overall *Category 1* and *Category 2* scores as dependent variables.

- When grouped by *Gender*, results indicated that the *Category 1* scores of male participants *(Mdn = 56)*, did not significantly differ from the *Category 1* scores of female participants *(Mdn = 57*), $U = 328, ns\ r = -.02$. Similarly, *Category 2* scores of male participants *(Mdn = 67)* did not significantly differ from *Category 2* female participant scores (*Mdn* = *66*), $U = 321, ns\ r = -.03$.
- No significant differences were reported when participants were grouped by *Race_Ethnicity*, *Annual_Income*, *Age*, *Parent_Educational_level*, *Class_Standing*, *Disability status and LGBTQIA+_membership*. However, there was a significant difference observed between the two most prominent *majors: Computer Science and Information and Technology.*
- Results indicated that the *Category 1* scores for students in *Computer Science* were significantly lower *(Mdn = 56)* than those from students in *Information and Technology (Mdn = 68.5)*, $U = 75,\ p < .05\ r = -0.3$. Which means that students in *Computer Science consider Technical and Economic Technological factors* more significant (received higher rankings) than students in *Information and Technology*. Similarly, *Category 2* scores for students in *Computer Science* were significantly higher *(Mdn = 67)* than those from students in *Information and Technology* (*Mdn = 54.5)*, $U = 76, p < .05\ r = -0.3$. In other words, students in Information and Technology attributed more significance to *Sociological and Ethical Effects of Technology factors* than students in *Computer Science.*

V. Discussion

Principal Findings

The main objective of this study was to explore the perceptions of CSUDH Computer Science/Technology students on various technical, economic, social, and ethical real-world implications of technology systems, to evaluate the significance/relevance students attribute to *social and ethical* considerations in comparison to *technical & economic* ones in this context of technology in society. Through this evaluation, we examined if the pattern of "inattentional blindness," currently aggravating the technology sector [13], is also observed among university students of a public and federally designated Hispanic Serving Institution such as CSUDH.

The results of this study indicated that there was a significant difference in the cumulative *Category 1* and *Category 2* scores.
Overall, participants attributed greater significance to *Category 1* statements that are related to *technical and economic* considerations, in comparison to those in Category 2, associated with *social & ethical* considerations. However, this relationship yielded a medium effect size $r = 0.4 \pm .1$
We also found a significant difference in the cumulative *Category 1* and *Category 2* scores between students in *Computer Science* and *Information and Technology*.
Students in *Computer Science* considered *Category 2* statements related to *Technical and Economic Technological factors* more significant than those in Category 1, associated with *social & ethical* considerations. In contrast, students in *Information and Technology who overall* considered *Category 2 Sociological and Ethical Effects of Technology factors* more significant. These relationships also yielded a medium effect size of $r = 0.4 \pm .1$.

These findings are consistent with the first part of our hypothesis which anticipated that the pattern of "inattentional blindness" observed in the technology sector, might also be persistent among CSUDH students in the Computer Science/Technology related fields. In other words, CSUDH students in the Computer Science/Technology related fields attributed greater overall significance to *technical and economic* considerations of technology systems, in comparison with *social and ethical* ones.

Study Limitations

This study had several limitations: The limited sample size and the largely homogenous demographic backgrounds. Over 80% of our study subjects were heterosexual Hispanic or Asian male students in Computer Science. Another limitation was the lack of a control group, such as students in the social sciences or humanities. A control group could have allowed for a more in-depth analysis.

Conclusion

"Inattentional blindness" is used to refer to the current phenomenon of system developers who are not necessarily trained on subjects such as gender, criminality, intersectionality, etc., and often fail to identify critical social and cultural considerations of their developments, causing them to take narrow technical approaches to deal with complex social problems [6].
As such, the main objective of this study was to examine the materialization of this phenomenon in higher education. And investigate if the pattern of "inattentional blindness" currently aggravating the technology industry [13], is also observed among CSUDH students, or if the respective intersectional identities of a more diversified student body have a detectable effect on students' perceptions of social and ethical implications of technology.

Our investigation indicated that students in these related fields attributed a greater overall significance to *technical and economic* considerations in comparison with *social and ethical* ones. A compelling indication that "*inattentional blindness*," might also be a considerably persistent pattern among students in higher education, even those attending a public and federally designated Hispanic Serving Institution in Los Angeles County.

While we recognize the importance of the continued efforts to diversify the tech workforce, our study results indicate that is also crucial to acknowledge that simply advocating for increased inclusivity and diversity in these fields, will not completely solve the problem of "inattentional blindness". Group membership does not automatically translate to individual awareness of the ethical and social considerations of technology.

These findings highlight the possible limitations of relying solely on diversification efforts to mitigate algorithmic bias. And further emphasize the urgency for institutions of higher education to evaluate the role current curricula play in the Automation of Inequality.

VI. References

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