Causal effect of racial bias in data and machine learning algorithms on user persuasiveness & discriminatory decision making: An Empirical Study

Kinshuk Sengupta  
Microsoft Corporation, India  
kisengup@microsoft.com

Praveen Ranjan Srivastava  
Indian Institute of Management, Rohtak  
praveen.ranjan@iimrohtak.ac.in

Abstract

Language data and models demonstrate various types of bias, be it ethnic, religious, gender, or socioeconomic. AI/NLP models, when trained on the racially biased dataset, AI/NLP models instigate poor model explainability, influence user experience during decision making and thus further magnifies societal biases, raising profound ethical implications for society. The motivation of the study is to investigate how AI systems imbibe bias from data and produce unexplainable discriminatory outcomes and influence an individual’s articulateness of system outcome due to the presence of racial bias features in datasets. The design of the experiment involves studying the counterfactual impact of racial bias features present in language datasets and its associated effect on the model outcome. A mixed research methodology is adopted to investigate the cross implication of biased model outcome on user experience, effect on decision-making through controlled lab experimentation. The findings provide foundation support for correlating the implication of carry-over an artificial intelligence model solving NLP task due to biased concept presented in the dataset. Further, the research outcomes justify the negative influence on users' persuasiveness that leads to alter the decision-making quotient of an individual when trying to rely on the model outcome to act. The paper bridges the gap across the harm caused in establishing poor customer trustworthiness due to an inequitable system design and provides strong support for researchers, policymakers, and data scientists to build responsible AI frameworks within organizations.

Keywords: bias in data; machine learning; human-AI; interpretability; fairness

1. Introduction

Bias in the dataset in any variation has significant consequences when a machine learning model is trained without a proper mitigation strategy. The existence of racial or gender bias in language data has been recently studied in the context of an individual's perception while dealing with AI-based systems such as recommendation engines. It holds AI systems
accountable and questionable due to gender or racial bias (Gupta et al., 2021). The study argues the adverse consequences of wrongly presented outcomes from AI-based systems influencing users' judgmental quotient. Since linguistics is part of core social behavior and is likely a primary medium through which individuals communicate or express views for social categorization, it becomes critical to study the lateral influence further when humans interact with systems designed on linguistic datasets. A recent study by researchers in Facebook AI Labs argues how a significant portion of textual data exhibits varied social information in the context of dialog data (Dinan et al., 2020). Such datasets, further when used for training machine learning models or NLP algorithms to solve core business or decision-making problems, are vulnerable to the carry-over effect due to the absence of contextualization capabilities of AI systems. The rise of data and advancement in machine learning algorithms has led to a critical data and algorithmic bias issue. There is limited empirical evidence proving how algorithms exhibit various kinds of bias learned from data (Kordzadeh & Ghasemaghaei, 2021). The machine learning systems show gender-specific bias (Butler et al., 2018) or racial bias (Manzini et al., 2019) impact decision-making due to the limited explainability of models. A study from existing literature indicates the vast impact of biases in models, such as racial discrimination in differences within the communication styles in sentiment analysis interpretation (Guerini, Gatti, & Turchi, 2013) and products review discussion (Yang et al., 2015). The study focuses on discovering the influence of biases in machine learning systems and their impact on business decision-making. An important aspect of machine learning systems identified in this paper will be exploring how racial discrimination impacts NLP and machine learning models' efficacy and whether biased models influence the discriminatory decision-making process.

The viewpoint from previous literature is evidence to demonstrate that influence of racial bias in various stages of a natural language processing (NLP) system starting from training, leveraging pre-trained models such as BERT, RoBERTa, GPT3, or word embeddings, and in subsequent algorithms are studied by many authors (Zhao et al., 2018a; Garg et al., 2018). Considering the depth of the influence, it becomes an important aspect to investigate how to identify the impact of such biases in the machine learning systems that can further develop different types of problems leading to unethical decision making in various contextual scenarios (Blodget et al., 2021). Due to biases, a machine learning system tends to select the wrong choice, creating a massive problem in business decision-making. Bias is an impurity of machine learning technology, and it is essential to eliminate the biases to make this system perfect. Elimination of biases will improve the overall decision-making process of artificial intelligence technology (Haenlein & Kaplan, 2019). It is imperative to understand how the NLP system becomes biased towards some specific options or criteria. Hence, understanding and
identifying the impact of bias in artificial intelligence-based algorithms is the main motive of this study. The paper focuses on identifying and eliminating different bias factors in artificial intelligence technology from an overall aspect.

The article exemplifies the critical implication of data and algorithmic bias in real-world situations, leading to unfair predictions causing discriminatory decision-making using the deployed models and articulate post-deployment impact in decision-making scenarios. The focus and motivation of the study will encompass identifying attributes of racial bias or stereotyping, exploring questions from identifying presence in the data and machine learning models. Preliminary literature exemplifies racial discrimination in algorithms developed for various problems like job ads, core recruitment, and promotion recommendation systems. Here, the models inherently learned to create biased hiring decisions towards males than females' candidates (Leavy, Meaney, Wade & Greene, 2020) or black vs. white candidates. Another researcher studied the danger of racial and economic inequalities influenced decision-making via algorithm (Bigman et al., 2021). The research work discussed above indeed is a broader problem in the current societal setup. It thus needs focused research interest to solve problems at multiple levels starting from identifying biases and scoring datasets to measure impact on model's consumption once any learning models trained on biased datasets. The upcoming section discusses the background of previous work in the space of racial bias and machine learning explainability.

2. Background

The section provides comprehensive literature on the primary research conducted in biases in the dataset, machine learning model, and intrinsic influence on fairness and explainability (Varley & Belle, 2021). Various research work critiques the importance of data mining in democratizing fairness in sociotechnical systems (Selbst et al., 2019). Thus, it becomes crucial for any business to leverage AI-based systems. Further studies have proposed that an automated decision can develop discriminatory behavior towards specific groups depending on ethnicity or gender. The text mining algorithms make certain modeling assumptions, creating particular situations where these constraints are not satisfied. The authors (Park et al., 2018) have performed experiments to outline three realistic scenarios and identified that a biased process could produce discriminatory models. Further, gender has shown innumerable impacts in various stages of the linguistic and machine learning lifecycles such as corpora, an ML task, or AI-systems (Chang et al., 2019; Costa-jussa´, 2019; Sun et al., 2019).

According to the authors Jiang & Nachum (2020), in many cases, different data sets include biases due to which unfair disadvantage is there for specific groups. The authors have
developed a mathematical formulation to understand how a preference exists in datasets. To perform this, the authors have assumed unknown, underlying, and unbiased labels that intend to provide proper tags but may also include biases against a particular group. Furthermore, preferences in data suffer limitations for corrections by modifying the data points without making any changes in the labels. In the present context, studies have shown that training on a limited data set corresponds to exercise an unbiased level in machine learning classifiers.

AI and NLP systems need to improve upon to combat discriminatory responses. Such systems preserve concern regarding differential responses leading to harmful impacts on vulnerable communities in an online setup where user interaction is prima-factor (Park et al., 2018; Liao et al., 2020). This type of concern becomes more harmful when automated decision-making systems utilize sensitive data to provide some core service leading to the identity of harm (de Laat, P.B., 2018). Earlier work from researchers (McDuff, Cheng, & Kapoor, 2018) has identified that machine learning models can develop bias due to the datasets used to train them. There is a massive issue regarding implementing machine learning technology in different sectors for the decision-making process as it can perform poorly on conservative populations and minorities in nature. Thus, such a type of decision-making system possesses a higher risk for this type of community. Considering the situation, the authors have proposed a high-fidelity computer simulation for integrating and diagnosing biases within machine learning classifiers. The authors presented a framework that can leverage Bayesian parameter search for efficiently characterizing high dimensional feature space. It is very much helpful in identifying performance-related weaknesses quickly and efficiently. The authors have used commercial face application programs to present their idea to identify demographic bias within the machine learning context. Racial prejudice has a significant impact on multiple sectors such as recruitments (Bertrand & Mullainathan, 2004), digital services, educational industry, legal services (Rice et al., 2019), and catering to deep societal problems through machine learning-based HCI systems for a mental health assessment (Adamou et al., 2018). Research work by Espinoza, da Luz Fontes, and Arms-Chavez, 2014 identified that racial bias could impact the ability and efforts of teachers regarding the explanation for students. Exciting research has shown that racial discrimination can generate different attribution for male versus female students in the education system. Here, such bias has been very prevalent due to human tendency and committed by the parents, teachers, and students.

In a typical practical scenario, an NLP model specifically counts on multiple assumptions. First, it argues that the data population to remain similar in future versions of the datasets when the model training happens. Secondly, the training data likely exhibits the overall population evenly. If this assumption fails to hold, the models would also fail to function accurately (Kelly et al., 1999). The following belief tends to be convincing only if the historical
data resembles the population of the users in the real-world context. Thus, the training data should depict an equal proportion of positive and negative scenarios compared to a real-world context, i.e., the population distribution of variables like ages, males vs. females, Black vs. white, or poor vs. rich data points remain balanced.

In the recent past, authors proposed how to detect misinformation using machine learning models. A research study recommended using a long short-term memory (LSTM) model to see wrong information from textual datasets (Bahad, Saxena, & Kamal, 2019). The proposed model detects complex patterns in the textual dataset by assessing a particular sentence bi-directionally and thus works better than unidirectional LSTM models. Another research work (Ma, Gao & Wong, 2019) proposed a model based on generative adversarial networks (GAN) to detect fake pieces of information on social media platforms and their consequences. Further, recent research carried out on the COVID-19 pandemic, many unintended biases and misinformation floating on social media observed suffer discrimination (Ayoub, Yang & Zhou, 2021). Systems developed for such data for fact-checking or medical claims show that perception and trust are two critical aspects of accepting results generated by all machine learning models (Kaur et al., 2021). A few limited studies have now started focusing on improving trust in model prediction by incorporating model explanation (Lai & Tan, 2019).

A detailed summary of corresponding research work in various fields is illustrated in Table 1 as described below.

**Table 1: Existing studies on racial bias and algorithmic decision making.**

| S.no | Study                                                                 | Reference                        | Context of Study      | Implications                                                                 |
|------|-----------------------------------------------------------------------|----------------------------------|-----------------------|-----------------------------------------------------------------------------|
| 1    | Offensive and hate speech analysis: data to human-centric approach.   | (Kocoń et al., 2021)             | Cyber Bullying        | Discriminatory decision making by the system                                |
| 2    | Hybrid approaches for online harassment detection in highly unfair data | (Tolba, Ouadfel & Meshoul, 2021) | Cyber Harassment      | Detecting highly provoked context leading to stalking                      |
| 3    | Racial and economic inequality influencing algorithm decision-making. | (Bigman et al., 2021)            | Healthcare Systems    | Analyzing how algorithms are influenced by racial discrimination             |
| 4    | Study area-level twitter expressed negative racial sentiment with hate crime towards a group of people. | (Nguyen et al., 2021)            | Social Media Prejudice | Analyze Twitter feeds for racially discriminated tweets targeting a group of people |
| 5    | Online harassment detection in highly imbalanced data                | (Tolba, Ouadfel & Meshoul, 2021) | Cyber Bullying        | Classify harassing context in datasets                                     |
6. Racism in tourism reviews dataset (Li et al., 2020) Identify racially discriminated content from the reviews dataset

7. Deal with COVID-19 infodemic using explainable natural language processing models. (Ayoub, Yang & Zhou, 2021) Detecting false claim on Covid-19 through analyzing social media dataset

8. How AI can help prevent racial and gender bias, cooperation, and false confessions (Noriega, 2020) Detecting racial and gender bias decisions through AI models analyzing a legal dataset

In preliminary research work, user expectation and interactions are critical constructs examined in the context of search engines effectiveness (Fuchs, 2018) and their implicit impact of human biases complementing machine learning system interactions (Moffat et al., 2017). Thus, the work debates how machine learning systems imbibe negatively affected intermediate outcomes (Hellström et al., 2020). Consequently, literature does not provide adequate evidence for understanding how such a biased AI-based system can impact humans' social perception in the digital ecosystem where information drives business outlines. Further, gauging the relationship for the implied effect on user expectations, persuasiveness for the generated outcome, and coherent influences towards altered discriminated decision making when interacting with platforms helps end-users take acquiescent decisions.

3. Theoretical Foundation

The paper adopts two fundamental and critical information systems theories to support the cohesive nature of the proposed research model. The model is based on user interactions, the perseverance of information processed by machine learning systems, and the indirect influence of human biases. Norman's interactions theory captures the interaction phenomenon through evaluation variables and impacts any decision-making driven by the cognitive dissonance theory relying on cognitive processes component that helps to objectify confirmation bias or biased interpretation of information of an individual during the interaction session.

3.1 Norman’s Interaction Theory

The paper adopts Norman’s Interaction Theory (Massaro & Norman, 1990) as a foundational model, as illustrated in fig 1, to study the interfaces between people and computers, i.e., how humans interact with computers. Normans' interaction is derived from human-computer interaction to contribute to a critical influencer in the proposed research
model. The advantage of this model is that it can explain the interaction variable required for our research model, moderating the decision-making in the user's context. Previous work illustrates the relative importance of studying how users interact with an AI system. Researchers have come across various applicability in the space adopting the theory for designing human-centered AI-driven applications that would require profound interpretations of individuals’ developmental models of AI (Villareale & Zhu, 2021).

![Diagram of Norman’s Interaction cycle]

**Fig.1.** Norman’s Interaction cycle

The execution element is used to establish a goal, creates an intention for usage, specify the sequence of actions, and executing a plan for those actions. Next, the evaluation factor is further entitled to perceive the system's current state, interpret the system outcome, and later evaluate the system state or result. It is known to establish an ambiguous goal by forming an intent initially from the user's interaction viewpoint. Here, a user can control an actions sequence that they execute. When a system responds (in the context of this study, suggest topics and recommendations of movies), the user starts perceiving the new system state (information) and tries to interpret and assess it concerning the intended goal—another variable, i.e., cognitive dissonance moderates this interaction due to incorrect information presented by the autonomous system.

### 3.2 Cognitive dissonance Theory

The paper likewise embraces the theoretical foundation from Cognitive dissonance (Festinger, 1957) to support the causation effect of decision making due to cognitive biases in the evaluation process of information presented to the users. The model proposed that humans attempt for internal psychological consistency to function rationally in the real world scenario. Indeed, when a human finds contradictory information during any part of information evaluation, it increases cognitive dissonance leading to altered decision-making and technology adoption (Marikyan, Papagiannidis, & Alamanos, 2020). The theory provides grounding for studies related to machine learning systems witnessing the influence of cognitive dissonance in actual practice (Buczynski, Cuzzolin, & Sahakian, 2021).

### 4. Research model and hypothesis
As previously argued in the research gap section; An NLP model deliberately learns the biased context in the training datasets. The antecedents indicate the corresponding predictions witnessing similar bias outcomes (Bolukbasi et al., 2016). Grounding on previous work, the practical implications of an unaware machine learning model leads to undemocratic adoption (Abdul et al., 2018). The study proposed to examine rare yet critical gaps to be addressed, leading to insights around how racially biased dataset carries the gender dominance in the outcome when an NLP algorithm leverages such data for training. Further, the implication of unfairly trained models leads to inferior model quality and explainability. Thus, demonstrating discriminatory decision making and producing a negative signal for user's persuasiveness, as illustrated in fig 2.

4.1 Research GAP

The proposed research model focuses on how intelligent systems developed on biased datasets conjoined with anthropomorphisms influence the user’s perception and decision-making in the digital environment. The paper adopts two fundamental studies around how human-like biases influence the decision-making process in information processing (Shin, 2021) and how machine learning systems learn negative patterns from datasets due to contextual biases present in the dataset. The critique from various theories and research work provides the next set of opportunities to study the carryover-effect of any form of prejudice an algorithm can exhibit from a learned dataset in real-world situations (Hellström, Dignum, & Bensch, 2020). Additionally, recent research from MIT Labs establishes a relationship between how users and their narrative interpretation in virtual reality (VR) setup influences the actual outcome (Olson & Harrell, 2019; Sun, Nasraoui & Shafto, 2020). Thus, extending these constructs to support advances in the present study hypothesizes how cognitive dissonance and user interaction lead to alterations of decision-making and influence poor user persuasiveness for an NLP-based model in the digital ecosystem. The foundation of this study would further provide evidence of how cognitive biases impact the technology adoption process in the actual scenario (Marikyan, Papagiannidis, & Alamanos, 2020).

The study is grounded on the directional viewpoint discussed in future research work on algorithmic bias (Sun et al., 2020; Kordzadeh & Ghasemaghaei, 2021). The study brings in a new avenue of research discussing how that decision sensitivity task influences individuals and can determine how they perceive fairness in algorithms and decide whether they reject or accept recommendations set by algorithms. The authors propose an empirical evaluation of concepts likes human and technical characteristics that moderate the behavioral response. Further, they argue how the controlled outcome from algorithms and the perceived fairness of a model influences behavioral response simultaneously.
Two supportive propositions and relationships expressed in the paper (Kordzadeh & Ghasemaghaei, 2021) are further illustrated below,

a. Outcome control $\times$ Perceived fairness $\rightarrow$ Behavioral responses (discussed in Proposition 3)

b. Propensity to trust in technology $\times$ Perceived fairness $\rightarrow$ Behavioral responses (recommendation acceptance, algorithm appreciation discussed in Proposition 5)

![Diagram](image)

**Fig 2.** Research GAPs

### 4.2 Research model

The paper established the foundation from the theoretical support from propositions discussed above in the research gap. It focuses on evaluating how the fairness of a model/algorithm influences recommendation acceptance if they alter any decision-making and overall system adoption. The article brings in two significant gaps and hypotheses qualified for the current research work to study the influence of biases in the data, algorithm, and how users perceive the outcome to take real-world decisions, as illustrated in Fig 3.
**H1.** NLP model trained on a racially biased dataset inherently produces mediocre explainable and unfair models towards a specific race, leading to discriminatory decision making due to cognitive bias evaluation of the machine learning model outcome.

The first hypothesis probes that a model trained on racially biased datasets exhibit an implicit poor explainability towards a specific group of people(Savchuk, 2019; Prashan Madumal, 2019). The study hypothesizes that the trained model demonstrates unfair and inferiorly explained models, leading to discriminatory decision-making. In a typical machine learning lifecycle, feature engineering is an essential component of a successful model-building process. In text mining, trackless feature selection processes lead to significant noise and impact the models' learnability and generalizability (Mladenić & Grobelnik, 2003; Saarela & Jauhiainen, 2021).

**H2.** A biased NLP model produces racial sway predictions for the task such as sentiment analysis or topic mining and further influence the cause of destitute user persuasiveness due to inadequate information interaction and interpretation.

The second hypothesis frames the discussion around the concept of how trained biased models produces dominant outcomes for a specific ethnic group. The sparse text feature amplifies the cause of prevalent racial tokens in the learned model, creating unscrupulous responses as part of the model outcome (Tang & Liu, 2005; Packer et al., 2021). Further, the critical focus area of research work studied through WEAT(word embedding association test) analysis across various bias subjects(Tatman, & Kasten, 2017). The current paper further analyzes the conceptual understanding of the impact on actual user setup through experiments.

The research model further considers that the decision taken by the user during interaction with an AI system does alter the perception(Shin, 2021). The current research embraces two critical variables for moderation a) Cognitive dissonance, i.e., the way a human interacts with a biased conditional environment and, b) Evaluation of the system when users have a propensity to formulate intention around the response outcome generated from the interaction process due to cognitive bias(Kambhampati, 2019).
5. Data and Methodology

The study encompasses two-fold experimentation design; a) Software simulation through deploying an NLP model using the open-source movie review data, and b) running user-level experiments on the designed NLP task to study user-level interaction. A detailed view of the experiment design as discussed in the following sections below,

5.1 Data Statistics

Overall, 879 volunteers participated in the study based on preliminary elimination based on movie buff and mandatory data-sharing agreement consent. The target cohorts were confined to four regions EU, UK, USA, Asia, and six ethnic groups. The sample population comprises 443 women participants out of 879 with an age group between 41 and 50. The data analysis outlined detailed measures for treating anomalies, representation bias, or sampling bias through the random sampling technique. The descriptive statistics in Table 2 support the absence of any abnormality in the dataset out of the negative kurtosis implied field in major questionaries. Additionally, the data does not represent significant skewness across the domains, with slight deviation being treated in an experimental procedure to normalize the data.

Table 2: Data Summary

| Demographics | Ethnicity | Age | Gender | Preference | Genres | Movie Selected | Poor model outcome | Inferior Persuasiveness | Discriminatory |
|--------------|-----------|-----|--------|------------|--------|----------------|---------------------|------------------------|---------------|
| Mean         | 0.544     | 0.956 | 43.407 | 0.504      | 0.928  | 1.974          | 2.465               | 2.734                  | 1.578         | 2.156         |
| Standard Error | 0.017    | 0.024 | 0.143 | 0.017      | 0.009  | 0.044          | 0.057               | 0.050                  | 0.017         | 0.033         |
| Standard Deviation | 0.503  | 0.720 | 4.242 | 0.500      | 0.258  | 1.310          | 1.682               | 1.483                  | 0.494         | 0.988         |
| Sample Variance | 0.253   | 0.519 | 17.994 | 0.250      | 0.067  | 1.716          | 2.830               | 2.198                  | 0.244         | 0.977         |
| Kurtosis     | -1.849    | -1.068 | 0.232 | -2.004     | 9.088  | 0.996          | -1.232              | -0.704                 | 0.904         | 0.904         |
| Skewness     | -0.122    | 0.066 | -1.324 | -0.016     | -3.327 | 0.045          | 0.080               | -0.316                 | -0.316        | -0.316        |
| Count        | 879       | 879  | 879    | 879        | 879    | 879            | 879                 | 879                    | 879           | 879           |
| Confidence Level(95.0%) | 0.033 | 0.048 | 0.281 | 0.033      | 0.017  | 0.087          | 0.111               | 0.098                  | 0.033         | 0.065         |

5.2 Experiment Design

The paper embraces controlled lab experimentation as the preferred method to study both hypotheses by capturing user interaction. We developed an online recommendation and feedback system(RFS) tool to simulate the user-system interactions and data collection. The experiments were supervised for two weeks through crowdsourcing contributors identified as movie buffs based on pre-screen questions in the web tool and volunteered to participate in the study. The tool is designed to serve features of automated recommendations system of movies based on mandatory user's selection of genres, demographic, ethnicity, gender, movie pick and choose criteria, and few other variables. The movie reviews were a critical indicator for...
gathering the relationship amongst users’ choice and their typical selection criteria based on sentiment score, reviews, and other topics displayed on the OTT or digital web platforms. Seven genres were shown as part of the selection criteria (comedy, drama, romance, action, thriller, crime, and horror). The tool displayed three pre-configured movies on selecting a specific genre (e.g., drama as shown in Fig. 4), and users were asked to choose at least one film from the indicated option. The study implements two NLP models. A sentiment analysis model was developed using a Hybrid Heterogeneous SVM model post benchmarking with other algorithms shown in Table 4. A topic model trained on the IMDB movie reviews dataset was employed using LDA2Vec (latent Dirichlet allocation) chosen over classical LDA (Hasan et al., 2019).

**Fig 4.** RFS system recommendation page

### 5.3 Method

The initial facet of the analysis was to collect data and develop sentiment analysis and topic models using the review dataset. In Conjunction, the IMDB movie review dataset was chosen and combined with review data of pre-selected movies (Kagan, Chesney & Fire, 2020). On completion of data collection, the primary objective function was to test if the dataset collected represented racial biases in review text or not. The tool did not show the actual IMDB scores to the user to avoid disconfirmation (Jha & Shah, 2021).

#### 5.3.1. Racial Bias Estimator

The paper introduces a new racial bias estimator (RBE) as a scoring method based on co-occurrence statistics to examine the level of biases. The bias-estimator aims to compensate for the bias calculation in the dataset and augment the model building facilities and evaluation. Furthermore, the study leverage GloVe aka. "Global Vector for word representation"
(Pennington, Socher & Manning, 2014), an unsupervised model for locating vector representations of adjacent words used to obtain the closest term for racially biased concepts like African American, white, black man, racist, racism, afro, gator bait, ape, bamboula, boot lip, bounty bar, brownie, buck, and few other broader terms used to represent regional biases terms used to build a concept-term dictionary with two categories non-derogatory and derogatory. Moreover, word association measure calculated for each token matched in the concept-term dictionary and tokenized review dataset represented by,

\[ B(w, C, C') = \text{mean}_{c \in C} \cosine(\vec{w}, \vec{c}) - \min_{c' \in C'} \cosine(\vec{w}, \vec{c'}) \]

Here, \( \vec{w} \) denotes word-embedding for a topic \( w \), and cosine calculates the similarity coefficient for individual concept vectors compared for similarity. An illustrative scenario is for the term "Black" can have two nearest neighbors say "professional" and "drug dealer" the former token would be categorized as non-derogatory and the latter as derogatory. The next step is to calculate the relative measure of association between a set of reviews and a set of fair and discriminatory tokens and calculating word embedding association test(WEAT) statistics score represented as,

\[ B(w, A, B, C, C') = \sum_{x \in X} B(x, C, C') - \sum_{y \in Y} B(y, C, C') \]

The equation presents \( A \) and \( B \) as vectors for two different concepts. Then the model estimates the word co-occurrence matrix for measuring the frequency with reviews and categorized concept tokens within a sentence boundary range of 20 words and calculates the log probability of word co-occurred. The algorithm selected the top 15 frequently occurring terms in the dataset and then calculated the co-occurrence matrix for tokens coinciding within a sentence boundary of 30 words to obtain the estimator score. The estimator leveraged in getting scores for datasets collected for modeling and sampling. With reparative iteration, a balanced dataset was created with 50k observations categorized as derogatory and non-derogatory and partitioned into four different sets based on estimator score, as illustrated in Table 3.

**Table 3: Bias estimator score for dataset**

| S.no | Dataset Name | Total observation | Estimator Score(RBE) | Training Samples(80%) | Estimator Score(RBE) |
|------|--------------|-------------------|----------------------|-----------------------|----------------------|
| 1    | Reviews-50   | 50,000            | 0.798                | 40,000                | 0.787                |
| 2    | Reviews-40   | 40,000            | 0.793                | 32,000                | 0.791                |
| 3    | Reviews-20   | 20,000            | 0.872                | 16,000                | 0.851                |
| 4    | Reviews-10   | 10,000            | 0.778                | 8,000                 | 0.778                |
The scored dataset represented in Table 3. refers to selecting an appropriate training sample for the model building process; as part of the hypothesis, we chose a dataset with a high RBE score for the final model training. A detailed discussion on the modeling scenarios and supplementary analysis is in the upcoming sections.

5.3.2. Simulation and Analysis

The simulation exercise employed two different models. We selected the reviews-20 dataset with an RBE score of 0.851(Table 2) for model training. The rationale of using the specific dataset was to ensure that even post-sampling discriminatory terms imitate the effect in the model. Furthermore, a binary classification ML model trained was used to compute the sentiment scores on the reviews for each movie. As part of selecting the suitable model to be used in the RFS data collection system, a comparative analysis was conducted to benchmark different machine learning algorithms on the reviews-20 dataset to measure efficacy and select the suitable model for the task, as shown in Table 4. The objective of conducting a similar experiment was to understand how a model developed performs on the standard accuracy metric for binary classification sentiment analysis tasks. The study employs DPD aka. Demographic parity difference(Binns, 2018; Chouldechova, 2017) to measure the degree of biases exhibited by each trained model on the reviews-20 biased dataset. The significance of computing DPD was to examine the fairness metric for the machine learning algorithms evaluated. H-SVM is the preferred model for the sentiment task based on model comparison assessment on racial word features in the final selection stage. H-SVM achieved the best performance with an accuracy of 84.34% with a high demographic parity difference(19.12%). However, a model with 82.9% accuracy provided a better fairness metric(12.11%). A sentiment analysis model with the highest precision and lowest fairness were deployed in the RFS tool to study the phenomenon of user persuasion from the biased outcome. A fairness metric (demographic parity aka "statistical parity") calculated using the open-source Fairlearn package (Bird et al., 2020) as a critical metric to represent fairness in the model, as shown in Fig. 5 (Hardt, Price & Srebro, 2016). The demographic parity, aka 'statistical parity' difference, is a fairness metric that captures the difference between the extreme values across two groups or poor value of any specific group; in the background of the current study, it represents the feature “race” with derogatory and non-derogatory labels. The significance of evaluating a model for demographic parity through model comparison assessment illustrated in fig. 5 is to measure how fair the model is when trained on biased datasets. This measurement aided in choosing the deployment model.

Table 4. Model experimentation
| S.No | Dataset Name   | Model Name           | Accuracy | Demographic parity difference |
|------|----------------|----------------------|----------|------------------------------|
| 1    | Reviews-20     | H-SVM*               | 84.43 %  | 19.12 %                      |
| 2    |                | Random Forest        | 75.06 %  | 17.26 %                      |
| 3    |                | Boosting machine     | 85.12 %  | 18.58 %                      |
| 4    |                | ANN                  | 63.45 %  | 20.22 %                      |
| 5    |                | Linear SVM           | 81.23 %  | 16.11 %                      |
| 6    |                | Gaussian Process Classifier | 69.67 % | 18.35 %                      |
| 7    |                | QDA*                 | 75.78 %  | 17.11 %                      |

* Refer to appendix A.

Fig 5. Model fairness and accuracy metric

A vital element of the study, a topic model, displayed critical topics for each movie. A topic modeling model would determine what viewers or users are talking about for the recommended movie extracted from reviews on the IMDB website and social media sites (Albalawi, Yeap & Benyoucef, 2020; Vayansky & Kumar, 2020). The models intended to investigate how topics and related sentiments showed to a viewer could influence the decision to select a movie or cause alteration of choice during browsing. For this paper, LDA2Vec (Moody, C., 2016) becomes the default choice for modeling topics as it has overcome the challenges of the word2vec model while dealing with ambiguity and out-of-vocabulary problems. LDA2Vec leverages a combinatory approach to generate issues based on word2vec and LDA. The model uses Word2Vec to build vectors for words, documents, and relatable topics and provides equal weights to each document and a word as a combined approach to predict the subsequent context vector, instead of using only a term to indicate the context. Furthermore, choose an optimal model based on the model perplexity and topic
coherence scores (Table 5), proven metrics for the topic model task in NLP systems (Stevens et al., 2012). At this point, the model with low perplexity and high coherence score (Iteration 2) was selected for final deployment into the RFS system to capture viewers' interaction with the online tool.

**Table 5: LDA model selection metrics**

| S.No. | Dataset Name | Model Name | Number of Topics | Perplexity   | Coherence Score |
|-------|--------------|------------|------------------|--------------|----------------|
| 1     | Reviews-20   | LDA2Vec    | 10               | -6.2467      | 0.53294        |
| 2     | Reviews-20   |            | 20               | -8.8606      | 0.58120        |
| 3     | Reviews-40   |            | 10               | -5.4556      | 0.49327        |
| 4     | Reviews-40   |            | 20               | -7.7834      | 0.5010         |

Finally performed a comprehensive analysis of the viewers' interaction data. The assessment employed ordinary least squares regression analysis (OLS) to study the implicit impact of target and explanatory variables. The research further adopted a model explainer to discover how the model worked and found evidence of bias parity examined from user interaction data. The following section details the staged analysis to validate the association with bias and counter impact to the overall user's perception.

6. Results and analysis

As stated in the preceding section, the research paper adopted OLS regression (Bun & Harrison, 2018) to estimate variables' effect to confirm users' altered action of choosing a movie that displayed negative sentiment and derogatory topics leading to biased opinion. As part of experimentation, Pearson correlation was evaluated amongst the reference variables to examine the relationship between model performance, user's persuasiveness, and discriminatory decision making. The analysis in Table 6 shows, persuasiveness has a high correlating impact on variable discriminatory. Further, it also provides insights to confirm that a user found the model outcome unfair, which led to selection bias during the online session. As observed, regardless of the reviews shown to the users during the movie selection stage, the scores of poor model outcome still hold, confirming the influence of topics and the sentiment scores demonstrated for a specific movie.

**Table 6: Descriptive statistics, correlation matrix for the variables.**

| S.No | Variables | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  |
|------|-----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1    | Demographics | 1   |     |     |     |     |     |     |     |     |     |
| 2    | Ethnicity  | 0.070| 1   |     |     |     |     |     |     |     |     |
| 3    | Age        | 0.001| -0.017| 1   |     |     |     |     |     |     |     |
| 4    | Gender     | 0.005| 0.021| -0.001| 1   |     |     |     |     |     |     |
| 5    | Preference | -0.006| -0.036| 0.002| 0.024| 1   |     |     |     |     |     |
| 6    | Genres     | -0.006| 0.031| 0.002| -0.023| -0.026| 1   |     |     |     |     |
We created two distinctive OLS regression models to assess the relationship between target and predictor variables. The ‘persuasiveness’ variable characterizes the user's altered selection based on the scores shown to them. The variable ‘discriminatory’ signifies the importance of user feedback based on his experience during the selection process. Both the models yielded a p-value < 0.05 for associated variables a) poor model outcome, b) Ethnicity as shown in Table 7(a), and (b); there was further evidence towards how ethnicity influencing the discriminatory selection and poor user persuasiveness providing support to the hypothesis framework. The adjusted R-Square value for model-a was 0.876, and similarly for model-b 0.931, confirming the model could variance of the independent variable with a good fit.

**Table 7(a):** Model a (Inferior user persuasiveness and experience) using OLS Regression.

| Coefficients | Standard Error | t Stat | P-value |
|--------------|----------------|--------|---------|
| Intercept    | 0.666666667    | 7.08983E-16 | 9.40315E+14 | 0.00221 |
| Demographics | -1.37696E-16   | 1.21311E-16 | -1.135060261 | 0.2566 |
| Ethnicity    | 1.2567E-16     | 8.49221E-17 | 1.479826102 | 0.01392* |
| Age          | 4.06308E-17    | 1.43681E-17 | 2.872848929 | 0.00479 |
| Gender       | 1.09656E-16    | 1.2174E-16  | 0.900739122 | 0.36797 |
| Preference   | 9.46923E-17    | 2.37387E-16 | 0.398893522 | 0.69006 |
| Genres       | 8.90757E-19    | 4.65079E-17 | 0.019152827 | 0.98472 |
| Movie selected| -5.57028E-17  | 3.63924E-17 | -1.530618681 | 0.12622 |
| Poor model outcome | 0.333333333 | 4.12308E-17 | 8.08458E+15 | 0.00011* |

**Table 7(b):** Model b (Discriminatory Outcome) using OLS Regression.

| Coefficients | Standard Error | t Stat | P-value |
|--------------|----------------|--------|---------|
| Intercept    | 0.3333333333  | 1.41797E-15 | 2.35079E+14 | 0.0010 |
| Demographics | -2.75391E-16  | 2.42623E-16 | -1.135060261 | 0.2566 |
| Ethnicity    | 2.5134E-16    | 1.69844E-16 | 1.479826102 | 0.0122* |
| Age          | 8.12616E-17   | 2.87362E-17 | 2.827848929 | 0.0047 |
| Gender       | 2.19312E-16   | 2.4348E-16  | 0.900739122 | 0.3679 |
| Preference   | 1.89385E-16   | 4.74775E-16 | 0.398893522 | 0.6900 |
| Genres       | 1.78151E-18   | 9.30157E-17 | 0.019152827 | 0.9847 |
| Movie selected| -1.11406E-16 | 7.27847E-17 | -1.530618681 | 0.1262 |
| Poor model outcome | 0.666666667 | 8.24615E-17 | 8.08458E+15 | 0.0021* |

* Correlation significant at 0.01 level (2-tailed)
Subsequently, to examine the robustness of the model, additional statistical tests such as the variance inflation factor (VIF) test were conducted to avoid any possible implication of multicollinearity. The VIF for both the models was 3, indicating the absence of multicollinearity in the models. To evaluate if heteroscedasticity is present in the model, Breusch–Pagan test was conducted, and the test statistic (BP) score was 4.0761, and the corresponding p-value was 0.1271. Since the p-value > 0.05 level of significance, the null hypothesis is accepted and assumes heteroscedasticity is not present in the data.

The study adopts an alternative approach to confirm discriminatory and inadequate user persuasion from the interaction data. SHAP(Shapley Additive exPlanations) NLP transformer and Tree explainer trained on the reviews dataset to explain the models' causal effect and gain insights for user-persuasiveness analysis outcome (Lundberg and Lee, 2017). Next, to determine how the fairness metric adjustments impacted the deployed sentiment analysis model, Shapley Tree explainer was employed to gauge the influence of racial tokens in the model fairness. The step was essential as the model deployed was trained on all reviews about a specific movie displayed was taken into consideration for calculating sentiment score. The analysis depicted in Fig. 6 demonstrates how change or growing word feature space towards derogatory tokens leads to high demographic parity difference, i.e., low model fairness. Thus, providing justifications for a model shown to users using the entire reviews corpus could have impacted the sentiment scores in real-time. Reviews with highly derogatory tokens denoting imbalanced distribution towards a specific ethnic group lead to an unfair model that intends to lessen the user's persuasiveness and experience.

![Fig. 6. Influence of racial feature on the fairness of the model](image)

In addition to understanding how the topic model tends to impact outcome variables positively, the study exercised another separate experiment to measure the efficacy of the topics
shown to users during online integration. We performed the experimental validation by choosing two movies, a) Just Mercy and b) They hate U give. Further collected the corresponding movie reviews from the IMDB website. After that, trained SHAP NLP explainer using hugging face transformer pre-trained model for relationship estimation of variables. The explainer plot feature explored more relevant data through graphical analysis (Fig 7. a and b). The plot describes the importance of each token projection on the original text taken from the dataset considered in the topic and sentiment model. The analysis shown in the plot figures shows the regions of interest marked as red signify the text substring, which would increase the influence of biased tokens in the model response leading to more discriminatory topics. Whereas the blue regions indicate the decrease in the effect of biased tokens in the model response when included as part of the feature vector. The racial terms such as 'black,' 'guilty,' 'criminal justice,' 'poor,' 'minority class' influence the model's class biases.

Additionally, it is apparent to explain the presence of highly biased racially assertive features in the dataset. Consequently, the topic model was chosen with a high demographic parity difference(ref. Table 4 and Table 5) also exhibits the carrying-over effect of generating racially biased topics in a real-world system. The explainer feature and analysis confirm and support the hypothesis that the carry-over impact of an NLP model leads to insufficient user persuasion(destitute user persuasiveness) towards a movie on reading the topics and evaluating the corresponding sentiment score.

Fig. 7 (a). SHAP text plot for topic analysis on ‘Just Mercy’ movie reviews
7. Discussion and Conclusion

The paper provides evidence to support the proposed research model and corresponding hypotheses from data and simulations performed during the study. The results and analysis reveal that all NLP systems carry forward the coherent influence of biases from the data into a model outcome that positively influences the viewer's decision-making process due to cognitive bias and poor interaction with the information presented to the participants. For example, in this case, an online movie selection event. The influence of biased outcomes can change the user's selection process for specific information they might be searching for online.

7.1. Theoretical Implication

The research provides three significant contributions in data science, human-computer interaction (HCI), and the information systems field. Firstly, the paper offers shreds of evidence on how racial bias in the dataset is handed over in the machine learning models and producing discriminatory and unfair outcomes. Determining the social perception of AI systems in a digital context further extends support for establishing a relationship between algorithmic bias socio-behavioral constructs. Secondly, the paper provides unique contributions by providing evidence towards how unattended biases can cause massive harm due to users' behavioral consequences(Favaretto et al., 2019; Khalil et al., 2020) who are interacting with the system. The paper theorizes the implication of cognitive dissonance during an interaction process to exploit original human thinking and alters the overall perception. Thus, leading to negative decision-making due to discriminatory algorithmic outcomes. Several other distinctive
research works in the past have been presented, be it understanding fairness notion in sociotechnical setup (Selbst et al., 2019) or measuring the influence of the consumer review in online purchase setup (Helversen et al., 2018). The paper further provides pragmatic evidence towards the impact of cognitive bias in decision alteration during a human-computer interaction process. Additionally, it demonstrates a prominent effect of creating unrealistic user experiences due to physiological constraints generated from a prejudiced artificial intelligence environment. Lastly, the paper proposes a novel analytical technique for measuring and estimating racial bias in datasets to augment the foundational facet of bias mitigation strategy in the linguistic and machine learning modeling lifecycle.

7.2 Practical Implication

The practical implication of the current research gives immense space to data science practitioners, product analysts, and decision/policymakers within an organizational/societal setup to understand the causal effect of biases in an AI-driven model and the harm associated with such systems on products and services offered online. The biased system certainly does influence the customer's intention of selection or viewership in the OTT context. Further providing a directional viewpoint for the researchers, Machine learning practitioners to reform the way they develop and use machine learning systems in an ethnographic and design context (Lee et al., 2019). Creating more personalized, fair, and unbiased machine learning models, recommendation systems, or AI-enabled bots directly interacting with the customer would need to adhere to be ethical by design.

7.3 Limitation

The study's scope and experimentation have limitations in filling the gap around secondary factors contributing to discriminatory decision-making, i.e., unconscious bias or stereotyping in the current context. The topic has significant relevance in creating a sizeable societal impact in the digital ecosystem. Future research directions are further investigations around alternative cognitive biases in machine learning systems such as denigration, narrative fallacy, and head mentality. A similar study in different domains like financial assets management or education system where unconscious bias plays an overly critical role and online adoption of creating a digital experience for students using chatbots, AI-assistive teaching the need of the study becomes evident.

7.4 Conclusion

The paper's focus area was to examine how Human-AI interactions and biased systems affect an individual's decision-making. The findings demonstrate that machine learning systems do imbibe a carry-over effect when trained on racially discriminatory datasets. As a
result, when individuals start interaction with unmitigated AI-system, they tend to deviate from actual decision-making of making a choice; this happens due to poor articulation of information presented to the users. Furthermore, the paper contributes to the limited literature in algorithmic bias, responsible AI products and solution design, and fairness assessment in artificial intelligent systems. The study focuses on validating the implicit influence of cognitive disagreement generated during the interaction process of users in the context of online search and recommendation systems. The paper also introduces a novel method to identify and cope with unintended biases in a learning system. Lastly, the study provides a directional perspective for policymakers, researchers, and applied scientists across industries to set up a framework for designing and implementing applicable responsible AI frameworks for producing ethical ML models and algorithms.

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Conflict of Interest
The authors declare no conflict of interest.

Appendix A: Abbreviations

| AI      | Artificial Intelligence |
|---------|------------------------|
| OTT Platform | Over-the-top media service |
| RBE     | Racial Bias Estimator  |
| SHAP    | SHapley Additive exPlanations |
| OVR     | One-vs-rest            |
| GPT3    | Generative Pre-trained Transformer |
| BERT    | Bidirectional Encoder Representations from Transformers |
| RoBERTa | Robustly Optimized BERT Pretraining |
| GloVe   | Global Vector for word representation |
| LDA     | Latent Dirichlet allocation |
| NLP     | Natural language processing |
| H-SVM   | Hierarchical Support Vector Machine |
| QDA     | Quadratic Discriminant Analysis based classifier |
| DPD     | Demographic parity difference |
| ML Systems | Machine learning Systems |
| HAIX    | Human-AI Experience    |
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