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Tweeting AI: Perceptions of Lay versus Expert Twitterati

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Abstract

In light of the significant public interest in the AI technology and its impacts, in this research we set out to analyze the contours of public discourse and perceptions of AI, as reflected in the social media. We focus on Twitter, and analyze over two million AI related tweets posted by over 40,000 users. In addition to analyzing the macro characteristics of this whole discourse in terms of demographics, sentiment, and topics, we also provide a differential analysis of tweets from experts vs. non-experts, as well as a differential analysis of male vs. female tweeters. We see that (i) by and large the sentiments expressed in the AI discourse are more positive than is par for twitter (ii) that lay public tend to be more positive about AI than expert tweeters and (iii) that women tend to be more positive about AI impacts than men. Analysis of topics discussed also shows interesting differential patterns across experts vs. non-experts and men vs. women. For example, we see that women tend to focus more on the ethical issues surrounding AI. Our analysis provides a more nuanced picture of the public discourse on AI than can be gleaned from the media coverage.

1 Introduction

Due to the rapid progress in the field of AI, and especially its myriad applicaions touching our everyday lives, AI has become quite a hot topic of public discourse. While the media does cover this discourse, the coverage often tends to be dominated by the polarizing views of a few people with outsized megaphones. Understanding how the public at large perceives the costs and benefits of AI is critically important, as it can help define societal policy. While there have been some attempts at analyzing the views of lay public through opinion polls (e.g. (Gaines-Ross 2016)), they are often forced to be content working with very small samples.

To get a more inclusive sense of the public perception of AI, we decided to analyze the discourse on social media, especially since a large part of the public discourse on AI does happen there. Specifically, we collectd and analyzed over two million AI related tweets posted by over 40,000 users. In addition to a macro characterization of this whole discourse in terms of demographics, sentiment, and topics, we also conducted a differential analysis of tweets about AI from experts vs. non-experts, as well as a differential analysis of male vs. female tweeters.

Our resuls reveal several interesting characteristics of the current public discourse on AI: (i) By and large the sentiments expressed in the AI discourse are more positive than an average twitter discourse (ii) Lay public tend to be more positive about AI than expert tweeters and (iii) Women tend to be more positive about AI impacts than men. Analysis of topics discussed also shows interesting differential patterns across expertise and gender. For example, we see that women tend to focus more on the ethical issues surrounding AI.

Earlier work by Fast et. al (Fast and Horvitz 2016) conducted a longitudinal study of articles published on AI in *New York Times* between January 1986 and May 2016. This study revealed that from 2009 the discussion on AI has sharply increased and is more optimistic than pessimistic. Another recent survey (Gaines-Ross 2016) conducted by the Harvard Business Review on individuals who have no background in technology, also discussed the positive perceptions of these individuals toward AI. In comparison to these prior efforts, our analysis provides a far more inclusive and nuanced picture of the current public discourse on AI.

In the following, we describe the details of our study, including the way we collected the dataset, the demographics of the users in our dataset, analysis of twitter engagement statistics over this population, and, most importantly, sentiment and topic analysis–both on aggregate as well as differentiated across expertise and gender.

2 Data Collection

To crawl the users and their tweets about AI, we employ the official Twitter API[1] along with a frequency-based hashtag selection approach. Through the crawled data, we ensure that there is no user who belongs to both AIT and EAIT categories. Here we provide a high-level summary of our crawling process. A detailed explanation about the crawling and categorization of the data is explained in our arXiv version (Manikonda and Kambhampati 2017) of this paper.

[1]https://dev.twitter.com/overview/api

Lay AI-Tweeters (AIT): To crawl the tweets posted by AIT, we utilize a co-occurrence-based approach. We first utilize two hashtags *#ai* and *#artificialintelligence* to crawl 2 million unique tweets and iteratively extract the most frequently co-occurring hashtags. We consider the top-4[2] co-occurring hashtags – *#ai*, *#artificialintelligence*, *#machinelearning* and *#bigdata* to crawl a final set of 2.3 million tweets posted by AIT. Each tweet in this dataset is public and contains all the tweet-related information including the user bio. A tweet may contain more than a single hashtag which may lead to multiple occurrences of the same tweet in our dataset. So, we remove the duplicate tweets that resulted in a dataset of 0.2 million unique tweets posted by a unique set of 33K users.

Expert AI-Tweeters (EAIT): We manually compile a seed set of AI experts to crawl their friends (users they are following) who are also experts in AI using the snowballing approach to obtain 9851 unique experts. We label a given user as an expert by checking for these two vocabulary-based[3] conditions in their bio: 1) Vocabulary related to AI is used – for example, *machinelearning*, *ai*, *vision*, *researcher*, *#ai*, etc. 2) No vocabulary related to politics, business, news media are mentioned – for example, *reporter*, *organization*, *marketing*, *blockchain*, *breaking*, etc. We then use a keyword-based approach to classify this set of users as experts. This classification reveals that 35% of EAIT are *industry professionals*, 10% are *academicians*, 6% are *students* and rest are unclassified. For example,to categorize a user as an *academician*, we search for keywords such as 'professor', 'faculty', 'lecturer', 'teacher', etc.

Gender-Based Categorization: Research on gender differences especially their online behavior isn't new. In this paper, we investigate the differences between men and women (from both the expert and lay users categories independently) on how they tweet about AI. By considering the same data that we have for both AIT and EAIT, we categorize the users in our datasets as male or female by using the keyword analysis on their Twitter biographies. For example, we utilize keywords such as *female*, *woman*, *mom*, *daughter*, etc to classify a user as female. Similarly, *male*, *dad*, *son*, *father*, etc., to classify a user as a male. This approach resulted in 190 female users, 1169 male users from the experts category and 654 female users, 3823 male users from the non-experts category.

3 Characterization of Users

To understand the differences between expert and lay users, we first focus on characterizing the geographical and professional attributes of the user. These attributes provide a useful perspective about the users that could help us understand the insights obtained from the latter analysis. Table 1 shows the top locations of users who tweet about AI. At the AIT category, 6.77% are from Europe, 7.74% are from United States and 2.8% are from India. For the EAIT category, 11.17% are from Europe, 21.4% are from United States and 0% are from India. Thus, larger percentage of experts are from Europe and United States where as larger percentage of non-experts posting about AI happen to be from India.

User Category	Geographical Locations
AIT	USA (3.4%), India (2.8%), CA (2.6%), France (2.4%), England (1.9%), NY (1.8%), UK (1.6%), London (1.4%), Germany (0.9%), Paris (0.9%)
EAIT	CA (9.7%), NY (4.5%), USA (3.2%), England (2.8%), France (2.7%), MA (2.2%), UK (2.1%), London (1.9%), SF (1.8%), Germany (1.7%)

Table 1: Top-10 locations extracted from the user biographies who specified their geographical location

With respect to the profession, the top occupations for AIT (*manager, entrepreneur, consultant, founder, developer, engineer, writer, author, blogger, strategist*) and EAIT (*scientist, student, researcher, engineer, professor, cofounder, ceo, founder, director, entrepreneur*) show that majority of the Twitter users contributing to AI-related tweets are pursuing careers in technology.

User Category	Occupation
AIT	manager, entrepreneur, consultant, founder, developer, engineer, writer, author, blogger, strategist
EAIT	scientist, student, researcher, engineer, professor, cofounder, ceo, founder, director, entrepreneur

Table 2: Top-10 occupations extracted from biographies

4 Twitter Engagement

Table 3 shows the values of engagement metrics – *favorites* (or *likes*) received by a tweet, *replies* to a tweet and *mentions*. This table shows that tweets made by EAIT are more likely to be retweeted than favorited by the users on Twitter. 71.93% of tweets shared by EAIT are retweeted atleast once and 31.14% of tweets are favorited atleast once. AIT has 11.45% of tweets that contain atleast one user handle where as, EAIT has 67.57% of such tweets. This shows that experts are more likely to interact or engage in discussions with each other about AI on Twitter than AIT. Retweeting is one of the features to measure information diffusion which may suggest that *tweets posted by EAIT diffuse faster (higher retweet rate)* than the tweets posted by AIT.

Gender-based Evaluation of Engagement: We conduct a similar investigation as above at the gender-level for both sets of users in AIT and EAIT. This revealed that overall, AI-related tweets made by men have higher chances of getting retweeted (mean retweet value – 1.92 (male) vs 1.23 (female)) and favorited (mean favorite value – 2.41 (male) vs 1.8 (female)). Even though on average, men and women tend to engage with other users at equal percentages (*mentions* in their tweets), it is surprising to notice that tweets

[2] we found that the set of tweets obtained using these 4 hashtags are a superset of all the tweets crawled by using the top-15 hashtags

[3] composed by leveraging the AI vocabulary compiled here: https://goo.gl/ApCbnu.

	Min (Max)		*Median (Mean)*	
	AIT	**EAIT**	**AIT**	**EAIT**
Retweets	0 (1041)	0 (1701)	0.0 (1.5)	0.0 (3.28)
Favorites	0 (1268)	0 (1914)	0.0 (1.46)	1.0 (4.98)
Mentions	0 (9)	0 (10)	0.0 (0.63)	0.0 (0.54)

Table 3: Min (Max) and Median (Mean) values of Retweets, Favorites, Mentions extracted from AI-related tweets

about AI shared by men receive more retweets and favorites compared to female twitter users.

5 Optimistic or Pessimistic

We employ the psycho-linguistic tool LIWC to measure the emotionality expressed in the tweets. Tausczik et. al (Tausczik and Pennebaker 2010) in their work introducing LIWC mentioned that the way people express emotion and the degree to which they express it can tell us how people are experiencing the world. These metrics reveal that users categorized as AITs are more positive (65% greater than negative) and optimistic towards AI and its related topics. Tweets posted by experts show similar patterns as earlier but with relatively higher negativity compared to AIT (EAIT – *pos-index*:3.25; *neg-index*: 0.60); AIT – *pos-index*:0.82; *neg-index*: 0.248). It is also worth noting that, despite the general negative emotional content on Twitter as well as the pessimistic views about AI in the society, tweets focusing on AI are more positive than being negative.

User Type	*PA*	*NA*	*COG*	*INSG*	*Soc*
Students	3.14	0.70	23.06	13.91	3.77
Academicians	2.72	0.70	21.60	12.84	3.85
Industry Prof.	3.19	0.60	22.92	13.84	3.13

Table 4: Aggregated values of different emotion metrics– Positive Affect (PA); Negative Affect(NA); Cognitive. (COG); Insights (INSG); Social aspects (Soc) for three categories of experts – students; academicians; industry professionals

Alongside, we conduct a granular evaluation by comparing the emotion metrics between three sub-categories of expert users – *students*, *academics* and *industry professionals*. The aggregated values shown in Table 4 suggest that academics are relatively less positive and more social than users from the other two categories when tweeting about AI.

User Type	*PA*	*NA*
Male-AIT	29.94	7.01
Female-AIT	33.1	7.51
Male-EAIT	29.14	6.51
Female-EAIT	37.26	7.76

Table 5: Aggregated values of different metrics of emotion– Positive Affect (PA); Negative Affect(NA) for male and female Twitter users

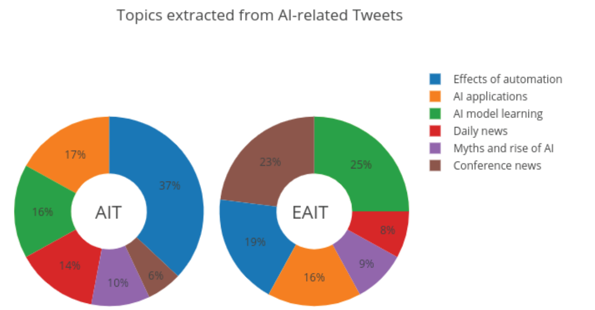

Figure 1: Topics extracted from the AI-related tweets

Gender-Based Evaluation of Optimism: Even though male users are equally negative compared to female users shown in Table 5, female experts (*pos-index*: 37.26) are 27.8% more positive compared to male experts (*pos-index*: 29.14). Similarly, female non-experts are 10.55% more positive ((*pos-index*: 33.1)) compared to male non-experts (*pos-index*: 29.94). Considering only the female twitter users, female experts are 12.6% more positive compared to female non-experts.

6 Topics heavily discussed by users about AI

We extract topics from the AI-related tweets to understand the user interests while talking about AI. To perform this, we utilize a *keyword*-based approach that looks for specific AI-related vocabulary in any given tweet. Figure 1 presents the six topics extracted from the AI-related tweets and their percentage distributions. These topics display that the largest percentage of tweets shared by AIT (37%) focus on the effects of automation on future. Where as, the largest percentage of tweets made by EAIT (25%) concentrates on the technical implementations of AI systems as well as tweets focusing on conferences & talks related to AI (23%). The emphasis on the applications of AI from industry are largely equal among both AIT and EAIT. The results show that users from AIT focus more on the effects of automation and general news about AI than the expert users.

Topics of interest to Men and Women: Based on the topic distributions for experts and lay users as shown in Tables 6 and 7 respectively, a large percentage of tweets posted by female experts are about the AI conferences. Male experts however, tweet a large percentage about the AI applications from the industry. When it comes to lay users, men and women discuss relatively equally about the emerging AI technologies and the future effects.

7 Co-occurring concepts

We employ the popular word2vec analysis (Mikolov et al. 2013) to detect relationships between words used in the tweets that are related semantically as well as syntactically. We first remove stop words from the tweets and train the Word2Vec model on the AI-related tweets posted by EAIT and AIT independently. We focus only on the top-4 popular

Topic	Men	Women
AI Books and Algorithms	8.7%	4.3%
Future of AI	15.2%	16.4%
Conference News	20.4%	39.4%
AI applications from industry	36.8%	22.4%
Technical implementations of AI models	18.9%	17.5%

Table 6: Topics and the percentage of focus on these topics by men and women from the **Experts** category

Topic	Men	Women
Future and effects of AI	31.8%	28.8%
Webinars and conference news	16.7%	14.0%
Daily news	10.3%	9.7%
Emerging AI technologies	27.4%	31.5%
Applications of AI	13.8%	16.0%

Table 7: Topics and the percentage of focus on these topics by men and women from the **Non-experts** category

terms in AI that are of interest to both academia and industry according to the recent literature (Manikonda, Deotale, and Kambhampati 2018). Table 8 provides the following insights on how AIT and EAIT perceive about the popular terminology in AI.

- *Agents* – experts talk about the different functional aspects of agents and their impact but AIT focus on the different types of agents.
- *Robots* – experts talk about the impacts of robots on the society where as, users in AIT are calling for the ban of robots before they take over the society.
- *Ethics* – experts focus on how ethics matter and that unethical or evil systems are worrisome.
- *privacy* – experts focus on the technical aspects of discovering patterns from the data and its impact on the privacy but AIT on the breakthroughs and lessons about AI.

Keyword	AIT	EAIT
Agents	Easier, Autonomous, Launched, Chatbots, Visit	Explains, Strong, Worry, Safer, Struggle
Robots	Life, Ban, Humans, Beat, Ethics	Embrace, Fear, Replace, Rise, Change
Ethics	Happening, Fascinating, Worry, Destroy, Life	Evil, Inequality, Worry, people, Matter
Privacy	Sense, Breakthroughs, Lessons, Connected, Predictions	Mining, Protection, Scientist, Labeled, Discovery

Table 8: Keywords and their co-occurring words

Gender-based association of the AI keywords: We train the Word2Vec model on tweets about AI posted by men and women from both EAIT and AIT independently. Through the Word2vec analysis, we found that female experts almost exclusively focus on ethics in AI. Surprisingly, their tweets about AI have no co-occurring words in the Word2Vec space with the keywords – *agents*, *robots* and *privacy*. While female experts tweet mostly about *ethics*, their male counterparts focus not only on *ethics* but also tweet about the *agents*, *robots* as well as *privacy*. When female experts talk about *ethics* they associate this word with – *today*, *taking*, *stop*, *conference*, *article*, *machine*, *listening*, etc displaying the emphasis on ethics.

On the other hand, non-experts regardless of their gender do not focus on privacy aspects but mostly focus on the robots. Female non-experts associate *robots* with *battle*, *threat*, *assistant*, *kids*, *industry*, etc suggesting the potential harm associated with the robots. However, male non-experts focus on the positive aspects of robots as they associate their tweets about robots with words such as – *latest*, *workforce*, *amazing*, *wow*, *future*, etc.

8 Conclusions

Given the popularity of conflicting debates about AI and the media coverage being exclusively distorted by a few people, it is not clear how the public perceives about AI. By conducting a large-scale analysis using posts about AI shared on Twitter to investigate the public perceptions about AI. Some of the key findings are: 1) Despite the pessimistic view about AI and the prevalence of negativity in Twitter posts in general, the discourse about AI on Twitter is overall positive 2) Experts are more negative in their AI-related posts than the lay users; 3) Women are more positive about AI than men especially, female experts focus more on ethics about AI. The insights obtained from this analysis sheds light on the positivity towards AI, in general but, few strongly opposing trends towards certain aspects of AI does exist. We hope that our findings will open discussions between AI researchers, designers, ethics researchers and policymakers and establish collaborations between them.

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