Measuring Gendered Communication Patterns on Enterprise Communication Platforms

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ABSTRACT

Much of the communication in organizations is now taking place on enterprise communication platforms like Slack and Microsoft Teams. These platforms enable modern teamwork, but may also exacerbate discriminatory practices. As discrimination can harm team outcomes, it is essential to study the impact that these communication methods can have. As a case study, we investigate gender discrimination in Mechanical Engineering – one of the least diverse subfields. We investigate whether traditional gendered communication patterns can be found on these platforms, as these patterns can communicate gendered differences that can lead to discrimination. Studying the Slack messages sent in mechanical design teams, we find that being a minority gender (identifying as not a man) is associated with an increase in some measures of emotional and agreeable communication, although not all, and there is no significant association with assertive communication. Future work will relate these patterns to discriminatory practices.

CCS CONCEPTS

• **Social and professional topics → Gender**; • **Human-centered computing → Empirical studies in collaborative and social computing**.

KEYWORDS

enterprise communication platforms, gender, communication patterns

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1 INTRODUCTION

Enterprise communication platforms (ECPs) – chat-like platforms used to communicate within an organization (think Slack or Microsoft Teams) – are rapidly becoming an integral part of most organizations' communication. Most recently, Slack reported that 77% of Fortune 100 companies use their platform[1], and Microsoft Teams reported over 270 million monthly active users[2]. While these platforms are essential to enable modern teamwork, specifically by lowering the barrier for interpersonal communication [1], they may also exacerbate discriminatory practices [5]. In fact, workplace discrimination has been found to be more prevalent online as it is often unmonitored [6], and women have been more likely to feel overlooked in virtual collaboration during the pandemic [3]. Discrimination and its consequences, even in terms of unbalanced engagement online, can harm group outcomes. For example, Woolley et al. suggest that collective group intelligence is predicted by the equality of conversational turn-taking and the number of women on a team [14]. With COVID-19 accelerating virtual communication, it is essential that we study the impact these communication methods can have on the equity and inclusion of team members.

To begin studying this phenomenon, we focus this work on gender discrimination in male-dominated fields. Women and minority genders are underrepresented in many technical fields, including engineering [7]. Language becomes particularly important when studying interaction that is primarily text-based: discrimination can be as obvious as slurs, or as subtle as the power dynamic reflected in the language we use [11]. To begin the investigation of gender discrimination on these platforms, we first search for the existence of traditional gendered communication patterns. These patterns may signal gender differences that lead to unequal treatment.

We build on Susan Herring's research studying gendered communication on online discussion boards. She found that many of the gendered patterns discovered in in-person communication also exist online, such as assertiveness, politeness, emojis, and level of interactive engagement [8]. Specifically, women send fewer messages , receive fewer replies, qualify and justify their assumptions, apologize more, and express support for others [8].

Recent research has investigated usage patterns on ECPs, related to language proficiency [10], overall engagement [9], and feedback or peer pressure [2], but these studies lack a focus on gender. In terms of discrimination, past work has investigated gendered patterns in online communities using qualitative analysis [8], which does not scale to large amounts of data. Thus, we develop an automated method. We aim to answer the research question: Do women and minority genders in traditionally male-dominated spaces display gendered characteristics on these platforms, such as more positive sentiment, more emotional text patterns, and less assertive

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[1] https://slack.com/blog/transformation/fortune-100-rely-slack-connect-build-digital-hq
[2] https://www.geekwire.com/2022/microsoft-teams-surpasses-270m-monthly-active-users-as-growth-slows-from-early-days-of-pandemic/

language? By presenting the results from one methodological attempt at answering this question, we hope to open a discussion on the best ways to further this work by using these identified patterns to analyze inequality on these widely-used platforms.

2 METHODS

The case study we are using is an undergraduate mechanical engineering capstone class at a major US institution. This presents an interesting context as the course itself often reaches gender parity (ranging from 45%-56% women in the years studied), but operates within the larger context of the mechanical engineering field, which is often cited as being one of the least diverse within STEM [7]. Thus, it is unclear whether we expect to see the same gendered communication patterns that exist in more male-dominated scenarios.

We use ECP data from six years of this course, consisting of public channel Slack messages from a total of 48 teams. The dataset contains over 341,000 messages, as well as metadata such as timestamp, reactions, and replies. We removed duplicate messages and bot messages, marked each user as a student or member of the teaching team, and connected Slack users to the self-reported gender information collected. For the purpose of this analysis we report on *"Minority Genders"*, which is the group comprised of all individuals who provided a gender but did not identify as a man.

To address our research question, whether *Minority Genders* display traditionally gendered communication qualities such as more emotion, less assertiveness, and more agreement [4, 8], we built linear regression models predicting different characteristics: overall emotion, assertiveness, and agreement. For each of these communication characteristics, we created a composite measure comprised of related measures proposed in past work. The complete list of communication characteristics used is shown in Table 1. Each measure in a composite was z-score normalized and averaged to create the composite measure. We conducted an internal reliability analysis for each composite measure, and we found low correlations. Measures that were removed to improve the reliability are marked with an asterisk in Table 1. To address this, we first built models to predict the composite, and then predicted each individual measure on its own. In the models, we controlled for individual differences (the course's gender breakdown, whether the user is a student or a teacher, their role within the team) and message characteristics (length in words, time of day, proximity to deadline, contains a question, contains an ask for engagement).

3 RESULTS & DISCUSSION

Table 2 shows the results of the models. We can see that being a *Minority Gender* is a significantly positive predictor of emotional communication, even when interaction effects are added. We can also see that this is driven by the *Minority Gender* being a positive predictor of using exclamations, multiple punctuation, and exclamation marks. Alternatively, being a *Minority Gender* is a significantly negative predictor of using affective adjectives, and not a significant predictor of absolute sentiment, using intense adverbs, emojis, or many emotional words. We see the best model fit when predicting the emotional composite; however, it is still objectively low. Even though being a *Minority Gender* is a significant predictor of emotion overall, this relationship is still weaker than some of the controls. It is not a significant predictor of the assertiveness composite, or any individual measure that comprises this composite. *Minority Genders* are significant predictors of the agreeableness composite, however it becomes insignificant on its own when interactions are added. This relationship is driven strongly by *Minority Genders'* use of expletives. While the assertiveness composite has a moderate model fit value, the agreeableness composite is poorly predicted by the variables included in the model.

These small effect sizes for these communication characteristics may be caused by the *Minority Genders* adapting their language to fit into the broader male-dominated university discipline, but may also represent uncertainty in the current method of measuring each characteristic. Additionally, the weak model fit values suggest that the use of these communication characteristics may be associated with features that we have not collected. Another noteworthy result is the variance in the strength and direction of gender as a predictor for measures that are generally understood to be similar. Of the nine measures of emotion, only three are positively and significantly predicted by gender, one is negatively predicted, and five are not predicted at all. This suggests the need to further identify robust linguistic representations for these features, which may require the translation of qualitative findings to quantitative measures.

This work provides some support for the existence of gendered communication patterns on ECPs in traditionally male-dominated environments, specifically in terms of emotional and agreeable communication. It also highlights a need for the translation of previous

Table 1: Communication characteristics examples and sources. * represent values that were removed during reliability analysis.

Communication Category	Examples	Source	Communication Category	Examples	Source
Emotional Composite			Assertiveness Composite		
Vader sentiment*		Vader[3]	Uncertainty	wonder, consider, suppose	[4, 12]
Flair sentiment*		Flair[4]	Hedges	well, kind of, sort of, possibly, maybe	[4, 12]
Affective adjectives*	adorable, charming, sweet, lovely, divine	[4, 12]	Tentative*	if, or, any, something	[13]
Intense adverbs	really, very, quite, special	[4, 12]	Certitude* (reversed)	really, actually, of course, real	[13]
Exclamations	good heavens, hey, oh	[4, 12]	Agreeableness Composite		
Emoji count	:slight_smiling_face:	[8]	Expletives	wow, whoa	[4, 12]
Many punctuation	???, !!!	[4]	Assent	yeah, yes, okay, ok	[13]
Exclamation mark count	!	[4]			
Emotion*	good, love, happy, hope, hate, hurt	[13]			

[3]https://github.com/cjhutto/vaderSentiment, [4]https://github.com/flairNLP/flair

Table 2: Summary of models. Green rows represent significant predictors in line with literature, yellow represents significant predictors that oppose literature. r^2 represents adjusted r^2. Coefficients are standardized.

Dependent Variable	Interaction?	*Minority Gender* Effect	Comparison Predictor	r^2
Emotional composite	No	$\beta = 0.05, p < 0.001$	message length: $\beta = 0.37, p < 0.001$, channel mention: $\beta = 0.15, p < 0.001$	0.18
Emotional composite	Yes	$\beta = 0.038, p < 0.001$	ask react: $\beta = 0.06, p < 0.001$	0.18
Exclamations	Yes	$\beta = 0.013, p < 0.05$	person mention: $\beta = -0.036, p < 0.001$	0.096
Many punctuation	Yes	$\beta = 0.024, p < 0.001$	question: $\beta = -0.018, p < 0.001$	0.0017
Exclamation mark count	Yes	$\beta = 0.059, p < 0.001$	ask reply: $\beta = 0.027, p < 0.001$	0.178
Affective adjectives	Yes	$\beta = -0.013, p < 0.05$	question: $\beta = -0.009, p < 0.001$	0.0002
Absolute Vader sentiment	Yes	$\beta = -0.095, p = 0.79$	role "System Integrator": $\beta = 0.043, p < 0.001$	0.003
Absolute Flair sentiment	Yes	$\beta = -0.004, p = 0.454$	role "Tool Officer": $\beta = 0.011, p < 0.001$	0.0004
Intense adverbs	Yes	$\beta = 0.005, p = 0.363$	channel mention: $\beta = 0.030, p < 0.001$	0.161
Emoji count	Yes	$\beta = 0.003, p = 0.595$	message length: $\beta = 0.044, p < 0.001$	0.021
Emotion	Yes	$\beta = -0.005, p = 0.389$	role "Information Officer": $\beta = 0.011, p < 0.001$	0.0007
Vader sentiment	Yes	$\beta = -0.010, p = 0.079$	gender breakdown: $\beta = 0.017, p > 0.001$	0.0037
Flair sentiment	Yes	$\beta = 0.000, p = 0.994$	proximity to deadline: $\beta = 0.008, p < 0.01$	0.0019
Assertiveness composite	No	$\beta = 0.002, p = 0.23$	question: $\beta : 0.022, p < 0.001$	0.0911
Assertiveness composite	Yes	$\beta = -0.002, p = 0.707$	staff: $\beta = 0.004, p < 0.05$	0.0912
Hedges	Yes	$\beta = -0.008, p = 0.125$	person mention: $\beta = -0.019, p < 0.001$	0.0706
Uncertainty	Yes	$\beta = 0.005, p = 0.331$	message length: $\beta = 0.162, p < 0.001$	0.0300
Tentative	Yes	$\beta = 0.004, p = 0.494$	morning: $\beta = 0.013, p < 0.001$	0.0006
Certitude	Yes	$\beta = -0.003, p = 0.617$	proximity to deadline: $\beta = -0.006, p < 0.05$	0.0001
Agreeableness composite	No	$\beta = 0.004, p < 0.05$	role "System Integrator": $\beta = -0.007, p < 0.01$	0.0002
Agreeableness composite	Yes	$\beta = 0.010, p = 0.058$	role "Slack Officer": $\beta = -0.006, p < 0.05$	0.0002
Expletives	Yes	$\beta = 0.015, p < 0.01$	ask react: $\beta = 0.007, p < 0.01$	0.0001
Assent	Yes	$\beta = -0.000, p = 0.993$	role "Information Officer": $\beta = -0.010, p < 0.001$	0.0004

qualitative findings to robust quantitative linguistic metrics in order to scale these methods to large data sets. Currently, we are working to relate these gendered communication patterns to unequal engagement, to understand whether these subtle differences are recognized.

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