Are We Equal Online?: An Investigation of Gendered Language Patterns and Message Engagement on Enterprise Communication Platforms

SHARON A. FERGUSON, University of Toronto, Canada
ALISON OLECHOWSKI, University of Toronto, Canada

It was previously hypothesized that gender differences – and thus gender discrimination – would disappear if communication was no longer in person, and instead was transmitted and received in the same format for all. Yet, even online, researchers have identified gendered language styles in written communication that reveal gender cues and can lead to unequal treatment. In this work, we revisit these past findings and ask whether the same gendered patterns can be found on modern communication platforms, which present a new set of engagement features and mixed synchronous capabilities. We quantitatively analyze 335,000 Slack messages sent by 845 individuals as part of 46 teams, collected over six years of a product design capstone course. We found little evidence of traditionally gendered communication styles (characterized as elaborate, uncertain, and supportive) from the minority-gender participants. We did identify relationships between message author gender, communication style, and message engagement — women and minority genders were more likely to have their messages engaged with, but only when using certain communication styles — suggesting complex power dynamics exist on these platforms. We contribute the first study of gendered language styles on Enterprise Communication Platforms, adding to the community's understanding of how new settings and emerging technology relate to team collaborative dynamics, and motivating future tool development to support collaboration in diverse teams.

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

Additional Key Words and Phrases: Enterprise Communication Platforms; Instant Messaging; Gender; Gendered Linguistics; Message Engagement

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1 INTRODUCTION

Will remote work be the great equalizer that it is often heralded to be? Many firms have released reports trying to answer this question [24, 27, 28]. The Women at Work 2022 report by Deloitte states that hybrid working is an opportunity to change the gender dynamics in the workplace [28]. In reality, workplace challenges for women remain, even in hybrid environments; for example, women are unsure of the expectations of them, and they lack the exposure needed to move up in the ranks [28]. 59% of women report experiencing harassment or microaggressions in the workplace

Authors' addresses: Sharon A. Ferguson, sharon.ferguson@mail.utoronto.ca, University of Toronto, 55 St George St, Toronto, Ontario, Canada, M5S 0C9; Alison Olechowski, olechowski@mie.utoronto.ca, University of Toronto, 55 St George St, Toronto, Ontario, Canada, M5S 0C9.

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[28, 43], and hybrid and fully remote workers experience more microaggressions than those fully on-site [28]. For example, these women reported having someone else take credit for their idea [28, 40]. Yet supporters of virtual work say that gender will not be as obvious — and thus will not be a factor in discrimination — when everyone connects and communicates in the same way.

Turning our focus to the role of communication in answering this question, Kira Hall in her essay on Cyberfeminism refers to two conflicting feminist responses to computer-mediated communication (CMC): one where it is a liberating utopia without gender norms, and one grounded in the reality of male-domination and the requirement for women-only spaces [42]. Previously, scholars predicted that the lack of non-verbal indicators of status and power on CMC platforms would have a democratizing effect on communication [39], particularly caused by anonymity [55], although others argue that even anonymity wouldn't be enough to eliminate gender inequality [93].

As language constructs and maintains gendered power differentials in society [39], the virtual communication platforms that teams rely on when working remotely could exacerbate the discrimination reported in face-to-face environments [28]. There are many reasons why workplace harassment may be worse online: there are no witnesses, there is an increase in informal communication [32], and the reduction in social cues may mean that communication is depersonalized, less social, and uninhibited [39]. Even in 1996, Herring described how men and women value different things when posting online, which influences their communication style; and there exists a general bias toward men's values [45]. We still see evidence of this today, with popular culture articles and social media prompting women to remove exclamation marks and passive language from their emails, in order to write more like men [116]. These gender-related language differences can be interpreted as differences in social or power status [39, 79]. People view language as indicators of belonging and respect — women may leave masculine environments because they are attending to these language cues that not only reflect, but also perpetuate, the inequalities in society [119]. In already male-dominated fields, like engineering [37, 86], obvious communication inequalities may hamper efforts to recruit and retain women.

In light of these hypotheses, in this work we revisit past findings and ask whether they still hold true on the CMC platforms that are widely used today. Enterprise Communication Platforms, group chat, and instant messaging are prominent topics in recent CSCW research [70, 71, 92, 102], and their rapid adoption among knowledge workers does not seem to be slowing [62]. Further, gender considerations [35], and particularly gendered communication [44, 91], have also been a focus of CSCW publications. Thus, here we investigate whether previously identified gendered communication patterns exist on modern Enterprise Communication Platforms, like Slack and Microsoft Teams. Research also shows how context matters in these studies; minority individuals begin to communicate like the majority gender over time [8, 64, 115]. Here, we investigate a unique context of gender-diverse teams within Mechanical Engineering, a traditionally highly male-dominated field [37]. We next aimed to understand whether the identified gendered trends influenced the minority-gender individuals' treatment on these platforms. While it was originally thought that anyone could "hold the floor" in online communication simply by sending a message, in reality, messages go unread and deleted. To hold the floor, you must hold your audience's attention, which, in this context, can be measured by continuing the conversation which was started [52]. Thus, we also measure how one's gender and communication style influence the level of engagement one's messages receives. Our research questions can be summarized as follows:

- **RQ1:** Do women and minority genders communicate in predictable ways on Enterprise Communication Platforms, as shown in past work?

- **RQ2:** Does one's gender, and gendered communication patterns, influence the level of engagement one's message receives on an Enterprise Communication Platform?

To address these research questions, we quantitatively analyzed 335,000 Slack messages from 845 individuals comprising 46 teams, collected over six years of a fourth-year product design course. We found limited evidence of expected gendered patterns of elaborate, uncertain, and supportive communication: women and minority genders use more exclamation marks and pronouns, while men use larger words and more affective adjectives. However, we found evidence that both the message author's gender and communication style are correlated with the amount of engagement that a message receives. Women and minority genders are more likely to have their messages engaged with — but not when the message contains supportive communication — although in general elaborate and supportive messages are most likely to be engaged with. We also report on engagement patterns by the gender of the individual engaging with the message.

We contribute the first study, to our knowledge, of gendered communication patterns on modern Enterprise Communication Platforms. We show that the long-held gendered communication styles may have changed since the initial studies, and therefore warrant revisiting in light of new modes of virtual communication. Conversely, we do find evidence for the existence of power dynamics, related both to author gender and communication style, suggesting that elements of the inequalities found on listservs and discussion boards in past work persist on modern communication platforms. We encourage future work to investigate gendered communication patterns on other modern communication platforms, and in diverse settings, to illuminate the mechanisms behind the departure of our findings from past work.

2 BACKGROUND

A note on the language used in the rest of this paper. As we deal with gendered linguistic characteristics, we use terms such as 'women' and 'men' instead of terms which describe sex such as 'female' and 'male'. Much of the early work in this field was conducted when it was most common to use the terms 'female' and 'male', even though the studies investigated socially-constructed gender. In light of current best practice, in the following section, regardless of the term used in the individual papers, we use gender terms to describe populations in these works as it best represents the variable analyzed.

2.1 Enterprise Communication Platforms

With the consistent digitization of work and growing prevalence of remote teams, fast-tracked by the COVID-19 pandemic, enterprises are rapidly adopting digital communication and collaboration tools [31, 121]. One category of tools experiencing rapid growth is Enterprise Communication Platforms (ECPs) [107], sometimes called enterprise social networks [1, 2, 30], or enterprise social media [73, 94]. These terms represent a variety of software used to communicate and collaborate within professional or enterprise contexts. Examples include Slack[1], Microsoft Teams[2], Google Chat[3], or Meta Workplace[4]. These often fall under the broad category of instant messaging [1] or group chats, though used in formal (workplace or educational) settings.

These tools are distinct from other CMC methods such as email or video-calling. Similar to face-to-face communication, they enable the rapid exchange of information [14, 114], feature informal vocabulary, incomplete sentences, and para-linguistic features of speech [114], and they lower

[1] https://slack.com/
[2] https://www.microsoft.com/en-ca/microsoft-teams/group-chat-software
[3] https://chat.google.com
[4] https://www.workplace.com/

barriers for interpersonal communication [19]. Further, they provide automated documentation of discussions, similar to email [33], and they can even include external tool integrations [1]. The growing use of ECPs provides researchers with a richer and more authentic dataset for studying team communication and collaboration dynamics than any traditional communication methods; yet, studies of these new platforms are only starting to emerge [18, 72, 109]. These studies have addressed emotion expression [92], non-verbal cues and emotional affinity [71], and linguistic mimicry [70, 102] on these platforms, but there has not yet been an investigation into the gendered dynamics that exist.

2.2 Gendered Communication Styles

The study of gendered communication styles is often said to have started with Lakoff in 1973 [66]. He argued that women avoid strong expressions of feeling, instead expressing uncertainty. This early research focused on face-to-face communication, where it was found that men speak louder and spend more time talking than women [63]. In a meta-analysis of face-to-face gendered communication styles, Leaper et al. also found that men talk more than women but differ in how they speak [67]. Women often use affiliate speech, which means to affirm or positively encourage others, whereas men use assertive speech, which aims to advance their own agency. In a second meta-analysis of in-person speech, the authors examined the hypothesis that women use more tentative speech, defined as qualifiers, hedges, tag questions, and intensifiers, reporting a small effect size to support this [68].

From reviewing this history of gendered language research, we identified three main categories of findings: Genders vary in their use of elaborate, uncertain, and supportive communication — we describe each below in turn.

Past work has shown that women tend to be more elaborate in their communication [39, 61, 79, 84, 87, 99, 114]. For example, many studies have found that women are more emotional in their written communication [39, 61, 65, 68, 69, 79, 82, 84, 87, 99, 114, 115], as measured in multiple ways. Women use more emoticons or emojis [3, 9, 51, 53] (though there is some contradictory results, one study found that men use them more often [59], and another found that men use a more diverse set of emojis [117]), more affective adjectives (e.g. adorable, charming) [26, 85], more exclamation marks [95, 120], and more emotionally intense adverbs [26, 85]. Further, men were found to have a richer vocabulary [44] and use bigger words [61], while women were described as more expressive [34], using more judgemental adjectives [82]. Length and number of messages sent also provides evidence in this category. Researchers found that women post more messages on forums [13], send more text messages [10, 117], and have more turns in conversations [52, 110, 114]. However, the evidence for message length was less clear; some studies found that women send shorter messages [47, 48, 51, 52], while others found that men are more brief and succinct [65, 79, 80, 82].

Another group of evidence explains that women's communication is more uncertain than their peers' [47]. There is a large body of work, beginning again with Lakoff [66], that describes how women use 'hedgers' (e.g. maybe, sort of, could) more often than their peers [44, 47, 48, 53, 65, 79, 80, 84, 114, 115]. Along with this, women qualify and justify their opinions [51, 54, 81], use more intensifiers (really, very) [39, 65, 79, 89, 114, 115, 117], more negations [79, 87], more uncertainty verbs [68, 79, 80, 82, 111], more questions [47, 79, 111, 115], and speak more indirectly [65, 79, 89, 111]. On the other hand, men tend to share their opinion often [114, 115], and assert these opinions as facts [51]. Men also make strong assertions, in general [47, 48], use an authoritative tone [39], strong language [65], obligations (e.g. must, have to) [53], universal qualifiers [53], and boosters (e.g. of course, obviously, really) [53]. They also give more directions and instructions [54, 79] by using active verbs [98].

The third category characterizing the difference in communication can be described as supportive, or on the other side, adversarial communication [47]. Women are described as valuing politeness in communication [48], such as thanking, appreciating and apologizing to others [51], whereas men value things like openness and free speech, which are often in conflict with politeness [48]. Women are more likely to agree [13, 39, 51, 95, 96] and support others [39, 48, 69], offer compliments [9, 111, 114], use warmer and more positive language [39, 89, 91, 113], and use politically correct language [65]. This was once described as women communicating the message "I value and support you. I think this, but you may think otherwise" [48]. On the other hand, the authors described the message in men's communication as "I'll tell you that you are wrong" [48]. Men communicate in an adversarial way, by expressing more critical and opposed views [13, 49, 51], disagreeing with others [39, 103], using aggressive [65] or hostile [89] tones, and using swear words [36, 53, 100], insults [114, 115], or threats [51]. Along with this, research found that women are more likely to communicate about people [5, 6, 6, 44, 47, 54, 87], while men communicate about objects [5, 6, 54, 61, 87, 91, 100]. Women use more pronouns, particularly inclusive first person [47] and third person [6], while men use more "I" references [26, 61, 79, 81, 111] and self-promotion [47, 48]. While these differences may seem small, things as simple as pronoun choice can influence who gets credit — men say "I" while women say "we" [111].

While we have summarized numerous linguistic features that characterize gendered text, Hills [57] and Thomson et al. [114] show that the combination of these features is most predictive of gender, providing evidence for the idea of *gendered styles*. These three gendered styles — elaborate, uncertain, and supportive — are the categories we use in this paper's analysis. While these styles were identified in studies of written communication, much of this past work focused on outdated communication technologies like listservs and discussion boards [50, 51, 55], so it is unclear whether the same patterns will be found on modern communication platforms. In fact, some scholars argue that the features of instant messaging make some gendered conversation characteristics, such as turn-taking or interrupting, impossible to replicate [69]. We investigate this question in our work.

2.3 Context Matters

Not all studies of gendered communication have come to the same conclusions, leading to the understanding that gendered communication patterns differ by context and setting. Looking at how men and women give professional criticism, Mulac et al. found that half of their linguistic predictors were in the opposite direction than past research would suggest [83], highlighting the importance of studying various communication settings. Further, a study on MySpace found that while women and men communicated in gender-predictable ways in their forum posts, they did not on their about pages [36].

To this end, numerous studies have found that people adapt their language to the setting or context that they are in [49]. This aligns with Communication Accommodation Theory (CAT) [29], which suggests that individuals alter their communication style to reflect similarities between themselves and others. Thompson, Murachver and Green found that participants use masculine language when communicating with a man and feminine language when communicating with a woman [115]. This effect can be particularly salient in situations when individuals are seeking approval, or when personal identity cues are limited [114], such as on social media. On Twitter, users with linguistic styles that mimicked another gender were most often surrounded by this gender in their social networks [8, 64]. These findings lead us to predict that the women in our context may communicate in a masculine way, as they adapt to the masculine group and topic that they are within.

Further, it was previously hypothesized that we would not see gendered differences in communication styles in formal settings at all [5], based on the argument that while gender is more salient in

social communication, it should be less important when the goal of communication is to exchange information or complete tasks [114]. In educational settings, similar to ours, Guiller et al. found that men and women used similar linguistic variables when communicating on an asynchronous chat platform [39]. However, they found differences in the stylistic variables of communication, with women more likely to be empathetic, talk about personal experiences and their feelings, and men more likely to make controversial statements, use humour, and strong assertions. This study did not find evidence of sarcasm and flaming, as suggested by past work, perhaps because instructors (authority figures) were on the platform, which may deter students from this behaviour. Further of interest, this study did not find evidence that the minority gender conformed to the style of the majority gender, as would be predicted by CAT. This study analyzed a Psychology classroom that was dominated by women; the authors call for future work in traditionally male-dominated fields such as engineering, as we are studying here. Given these findings, and our classroom context with instructors present on the communication platform, we might expect gendered differences to be less pronounced compared to past work.

Another variable to consider in our study is the synchronicity of the platform. Many of these early studies were conducted using online discussion boards or mailing lists, which would be considered asynchronous in today's technological landscape. In asynchronous discussions, Herring found that men start, end, and control the conversation; however, she found that this distinction was less pronounced in synchronous environments — men and women sent the same length of messages, and got equal replies [51]. Savicki et al. found evidence of traditionally gendered communication patterns in a study using synchronous group chat, where participants worked in small groups to produce a product — similar to our context [98]. They argue that this context is important because there are fewer lurkers (non-contributors), and there is a specific task to work on where a product is produced at the end.

Given these trends, there are two characteristics of Enterprise Communication Platform use in our context that make the gendered communication characteristics hard to predict: Enterprise Communication Platforms are described as both synchronous and asynchronous [38]; and, the design teams studied are gender-diverse, but exist within a highly non-diverse broader field.

2.4 Outcomes

If the gender of an ECP participant is made salient by the language they use (for example, by invoking stereotypes or influencing expectations and perceptions [39]), this could influence the way they are treated on the platform. Many studies have shown that stylistic linguistic differences allow people to guess the author's gender [46, 48, 97], even suggesting that these cues are delivered every 3-4 lines of text written on a discussion board [46]. In one study [81], the authors showed that these language characteristics are implicitly understood and acknowledged by individuals. They asked participants to explain a picture "as if they were a man" and "as if they were a woman". They found linguistic features characteristic of the gender being represented, regardless of the actual gender of the participant.

Further, author gender and linguistic style influence how they are perceived by others: both men and women rated angry women as lower status than angry men, regardless of actual hierarchical position in the organization, and women's emotional reactions were attributed to their internal characteristics, compared to external circumstances for men [17]. In conversations, those who contributed more, and changed the topic most often, were perceived to have the most power [88]; however, even when women mimic these masculine communication tendencies, they receive backlash [16].

These perceptions, in turn, can influence how women and gender-diverse individuals are interacted with on these platforms. Reported inequalities exist on a number of online platforms: on the

Internet Movie DataBase, even when women communicated like men, they did not see an increase in likes or prestige [44]; men are retweeted more than women, with 63% of retweets originating from male users [74]; and, women's pull requests on GitHub were accepted more often than men's when gender was invisible [112]. Another study found that on academic threads, men received more responses, even on women-dominated forums [52]. Although women do not always receive less engagement: Selfe et al. found that those on an online conference system seemed to pay equal attention to women and men [103]; and in New York Times comment forums, women's comments received more recommendations than men's [91].

We can see how being engaged with on a platform is a sign that one holds power [52], and can be thought of as a form of interpersonal control [88]. These engagement discrepancies can discourage women from participating on these platforms and in discussions. Studies have shown that women initiate new topics only when they hold the power or are the dominant gender [52], and they commonly state intimidation as a reason for not participating [47]. Women are also more likely to stop posting if they do not get a reply [51].

There are consequences for this lack of participation: women feel a lack of belonging [119], and they leave professional discussions that may benefit them [52], sometimes creating and defending women-centred spaces for the type of discourse they value [45]. But we know that diversity is important: diverse teams are more creative and better at problem-solving [23, 56, 75]; are more productive [118]; generate more valuable inventions when the invention requires collaboration [108]; have higher sales and profits [58]; and contain more turn-taking [11].

In summary, studies of traditional communication modes have found that gendered language makes gender salient, drawing on stereotypical perceptions that can lead to unequal treatment, and further reduces participation, ultimately leading to less diverse discussions. In this work, we search for such evidence on Enterprise Communication Platforms.

3 METHODS

Here we describe the course setting where our data is collected, the data characteristics, and our analysis process.

3.1 Course Setting

This work analyzed Slack messages from six years (2016-2021) of a core product design course in Mechanical Engineering at a major U.S. institution. There are eight teams each year, and each team ranges from 15-20 students, with 10-15 additional teaching team members. In total, here we study 46 student teams and 845 individual students and teaching team members. In this course, teams work to develop a physical product — from ideation through to a functional prototype — within three months. While these teams are hybrid with set in-person meeting times, they are instructed to exclusively use Slack for all project- and team-related virtual conversations. This data collection was approved by the institutional review board, and students were aware that their public channel Slack messages were being collected for research purposes. During the consent process, students provided their gender. More details about these teams can be found in previous work [reference removed for anonymity].

This context is particularly suited for this research question as these students exist within the typically male-dominated field of Mechanical Engineering, with some studies citing that women make up only 8% of the field [37]. This class, however, achieves gender parity in all six years included in our sample. There are students in this dataset who identify outside of the gender binary, although a small amount. As statistically significant findings cannot be derived from the small sample size, for the purpose of this analysis, we report on "minority genders", which is the group comprised of all individuals who provided a gender other than a man (405 students identify as

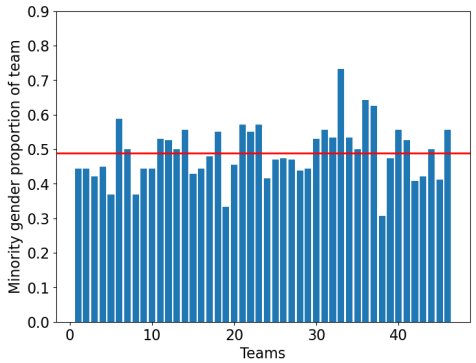

Fig. 1. Proportion of each team that identifies as a minority gender. Red line represents the mean of 0.49

a woman, and six identify outside of the gender binary). Figure 1 shows the proportion of each team that identified as a minority gender, with the red line indicating the average of all teams: 0.49 (standard deviation = 0.08). Thus, this class represents a gender-diverse subgroup within a less-diverse broader field; this unique setting has previously been understudied and thus, it is unclear whether we expect to see the same gendered communication patterns that exist in more male-dominated scenarios.

3.2 Data

Only *public channel* Slack messages are included in this analysis, meaning private channels and direct messages are excluded. We first removed any messages from participants who did not consent or did not provide a gender. This removed less than 6% of the messages sent. As this analysis exists at the individual message level, the removal of these messages should not impact the language used or engagement levels of other messages. Further, to determine whether the non-consenting individuals systematically differed from those consenting, we compared the gender breakdown of our participants to publicly available data about the greater Mechanical Engineering class. The Mechanical Engineering class overall contains roughly 48% women (they do not report minority genders) [77, 78]. Compared to our 49% average, this suggests that opt-out rates are equal across genders. Then, we removed duplicate and bot messages, resulting in over 334,000 messages; each with linked metadata such as timestamp and engagement. We consider two measures of engagement given the features of Slack: a threaded reply and an emoji reaction. Threaded replies allow users to send a message that is "attached" to a previous message, such that the entire thread can be viewed together. Slack only supports one level of threaded replies, meaning you cannot start a new thread from a message already within a thread. Emoji reactions are a function on Slack where users can add a virtual "sticker" to a message, which can be seen by everyone in the chat and are often used to communicate agreement or acknowledgement. We measure engagement for emoji reactions and separately threaded replies with a binary variable provided in the Slack exports, which disassociates the sender from the reply or reaction. Where counts were already anonymized and aggregated, data includes reactions from all course participants. In this engagement analysis, we do not study the type of reaction or the content of replies. Figure 2 contains general patterns in the data by year and by gender. The number of messages sent, replies, and reactions vary each year, experiencing a dip in 2020, while the average message length remains fairly consistent at approximately 15 words. Figure 3 shows that minority genders used the platform more: minority genders sent more messages (minority: 474 per person, men: 331 per person, $t = 6.10, p < 0.001$),

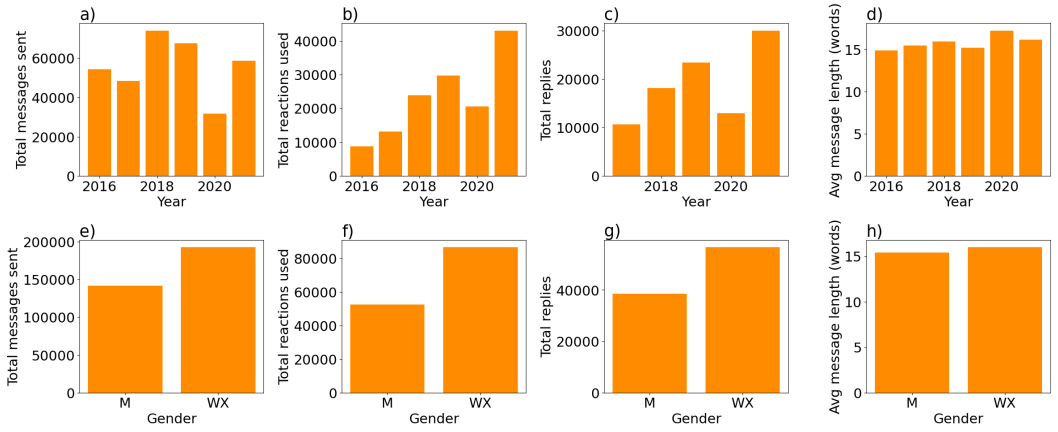

Fig. 2. General data characteristics. a) number of messages sent per year b) number of reacts per year c) number of replies per year (note that the reply functionality was not yet introduced in 2016) d) average message length in words per year e) total messages sent by gender f) total reacts by gender g) total replies by gender h) average message length by gender in words. M= Men, WX = Minority genders.

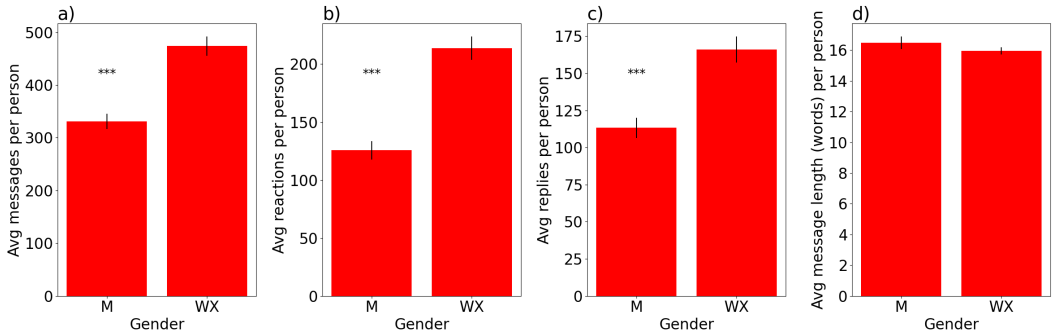

Fig. 3. Gender comparisons. a) average total messages sent per person, by gender b) average total reactions given per person, by gender c) average total replies per person, by gender d) average overall message length (in words) per person, by gender. M= Men, WX = Minority genders. Error bars represent one standard error. *** denotes a statistically significant t-test at $p < 0.001$.

used more reactions (minority: 214 per person, men: 126 per person, $t = 6.89, p < 0.001$), and sent more replies (minority: 166 per person, men: 113 per person, $t = 4.76, p < 0.001$), although there was no significant difference in message length (minority: 15.96 words, men: = 16.48 words, $t = 1.07, p = 0.283$).

3.3 Analysis

To address the first research question, whether gendered communication styles such as elaborate, uncertain, and supportive communication are found in Slack messages, we used linear regression models, similar to previous work [44]. For each communication characteristic, we matched qualities described in the literature (summarized in Section 2.2) to currently available natural language processing and linguistic measurements of these qualities. Each characteristic, definition, and source can be found in Table 1. These characteristics are broken down into three main styles, and

Table 1. Communication characteristics examples and sources. Characteristic sources represent literature where the component was suggested to be gendered, and the measure source describes where the measure was taken from. Entries without a measure source were simple enough to calculate manually. † represent values reverse coded when added to the composite.

Communication Category	Examples	Characteristic source	Measure source
Elaborate Composite			
Vader sentiment		[39, 68, 114, 115]	[60]
Flair sentiment		[39, 68, 114, 115]	[4]
Affective adjectives	adorable, charming, sweet, lovely, divine	[26, 85]	[26, 85]
Emoji count	:slight_smiling_face:	[51]	
Emoticon count	:) :/ :(	[3, 9, 53, 117]	[105]
Many punctuation	???, !!!	[39]	
Exclamation mark count	!	[95, 120]	
Emotion	good, love, happy, hope, hate, hurt	[39, 68, 114, 115]	[15]
Big words†	percent words 7 letters or longer	[44, 61, 87]	[15]
Adjectives	more, very, other, new	[81, 82]	[15]
Vocabulary richness†	unique words in message/total words in message	[44]	[44]
Uncertainty Composite			
Filler	rr*, wow, sooo*, youknow	[53, 84]	[15]
Cause	how, because, make, why	[5, 51, 54]	[15]
Tentative	if, or, any, something	[47, 53, 114]	[15]
Negate	not, no, never, nothing	[79, 87]	[15]
Discrepancy	would, can, want, could	[53]	[15]
Insight	know, how, think, feel	[79, 81]	[15]
Clout†	Language of leadership, status	[85, 90] [79]	[15]
Need*	have to, need, had to, must	[53]	[15]
All or None†	all, no, never, always	[53]	[15]
Certitude†	really, actually, of course, real	[53]	[15]
Intense adverbs	really, very, quite, special	[81, 114, 115]	[26, 85]
Uncertainty	wonder, consider, suppose	[79, 81, 82]	[26, 85]
Hedges	well, kind of, sort of, possibly, maybe	[65, 79, 80]	[66]
Apologies	sorr.*, apolog.*, my bad, oops	[47, 48, 65, 111, 114]	
Supportive Composite			
Assent	yeah, yes, okay, ok	[39, 96]	[15]
Agreement Words	right, yes, ya, yeah	[39, 96]	[76]
Disagreement Words†	right, yes, ya, yeah	[39, 49, 52]	[76]
Tone	Degree of positive (negative) tone	[39, 64, 113]	[15]
Prosocial behaviour	said, love, say, care	[39, 51, 65]	[15]
Politeness	thank, please, thanks, good morning	[48, 51, 89]	[15]
Cognition	is, was, but, are	[21, 39, 51, 69]	[15]
Pronouns	I, you, that, it	[5, 44, 87]	[15]
Negate†	not, no, never, nothing	[51, 52, 89]	[15]
Differentiation†	but, not, if, or	[84, 103]	[15]
Swear†	sh*t, f**kin*, f**k, damn	[36] [87, 100]	[15]
Determiners†	the, at, that, my	[5, 6]	[15]
Quantities†	all, one, more, some	[79, 81, 82]	[15]
Impersonal Pronouns†	that, it, this, what	[47, 89]	[15]
Social words	you, we, he, she	[5, 43, 89]	[15]
Affiliation	we, our, us, help	[47, 54]	[15]

we created a composite measure for each style by z-score normalizing and averaging all individual measures within the category. As women are described as more emotional [68, 114], we used two different sentiment analysis methods to capture the level of absolute emotion contained in

the text: a rule-based algorithm[5] [60] and an embedding-space algorithm[6] [4]. Emotion was also measured using the Emotion category in the 2022 version of the Language Inquiry and Word Count (LIWC) dictionary [15], and both inserted emojis and textual depictions of emotion were captured. Other measures of elaborateness include affective adjectives [85], multiple punctuation, exclamation marks, and adjectives. Elaborate characteristics shown to be associated with men's communication, and thus reverse scored, were big words [15] and vocabulary richness [44]. The uncertainty composite contained filler, cause, tentative, negation, discrepancy, insight, clout, need, all or none, and certitude categories from [15], with clout, need, all or none, and certitude reverse scored as they represent certain, as opposed to uncertain, communication. Lastly, intense adverbs [85], uncertain language [85], hedges [66], question indicators, and apologies were added from various sources. The supportive communication composite also is primarily composed of measures from [15], along with some measures of agreement and disagreement from [76]. In this composite, disagreement words, negation, differentiation, swearing, determiners, quantities, and impersonal pronouns are believed to represent masculine language and are thus reverse-scored. Note that negation is included twice — as a predictor of women's communication in the uncertainty composite, as suggested in [79, 87] (for example, used in the phrase "I'm not sure..") and as a predictor of men's communication in the supportive composite, as suggested in [39, 81] (for example, used in the phrase "that's not a good idea").

We conducted a reliability analysis on these composite styles and found that the individual measures were not highly correlated within our dataset, with Cronbach's α values ranging from 0.18 for the uncertainty composite to 0.45 for the elaborate composite. This may be because these characteristics are all components of a communication style, rather than multiple measures of the same characteristic, and a participant may have evidence of some components in their communication and not others. Further, as the goal of this work is to investigate whether gendered styles from past literature exist in this new setting, we kept individual measures within the styles they are part of from past work, as opposed to classifying new gendered communication styles. Given these low correlations, we first build regression models that predict each composite measure, followed by predicting each individual measure within the composite. To correct for multiple tests, and prevent an increase in Type 1 error [12], we set our significance value to $p = 0.05/\#oftests$, which in this case is 45. Thus, only results with $p < 0.0011$ were considered significant in this case. In each model, we control for sender and message fixed effects, and the interaction between these and gender, which are described in more detail below.

To address the second research question, whether minority genders' messages receive less engagement, we used logistic regression to predict the engagement a message receives. We built models predicting whether a message received at least one threaded reply or one emoji reaction. Messages sent in 2016 were removed from the replies analysis as the functionality was not yet introduced. We also removed messages that were replies themselves from this analysis, as Slack does not support multi-level threads. These are three-step models: we first predicted each engagement measure using only gender and fixed effects; we then added the gendered characteristics from the first research question into the model to investigate whether these textual characteristics mediate the relationship between gender and engagement. Lastly, we added interaction effects between gender and communication characteristics. As a final analysis, we were interested in who was engaging with the messages. For only the subset of messages that were engaged with, we predicted the gender of the person who engaged with the message (binary prediction— minority gender or

[5] https://github.com/cjhutto/vaderSentiment
[6] https://github.com/flairNLP/flair

not) and looked at whether the message author's gender was a significant predictor. In short, we answer the question: were minority genders replying to other minority genders?

In each model, we controlled for individual differences and characteristics of the messages. The individual fixed effect variables consist of the gender breakdown of the team the message author was in (Figure 1), as literature has shown that the gender breakdown in a group can influence both the communication styles [115] and level of engagement [91] in online communities. We also controlled for teaching team member or student, student roles within the team (one of eight roles), and whether the student was a high Slack contributor (sent more than the median number of messages per person for their year). The message fixed effect variables include the length of the message (in words), the time of day it was sent (morning, afternoon, evening, or night), the proximity to a deadline measured in seconds (as we may assume that messages sent closer to a deadline require a response), whether it contains characteristics of a question, such as question marks or questioning words (as we may expect messages with a question receive more responses than those without), and similarly, whether the message contains the word 'react' or 'reply' (as users often ask teammates to vote by reacting to a message, or may explicitly ask for a reply). Lastly, we control for the phase of the project, as a proxy of time, as well as year. This totals 22 controls.

4 RESULTS

We report our results for each research question in turn, beginning with the presence of gendered communication styles, followed by the influence these styles have on message engagement.

4.1 RQ1: Gendered Communication Styles

The first research question we aimed to answer was whether traditionally gendered communication styles can be found in Slack messages. The results from these models can be found in Table 2. Due to the significant number of individual regressions and predictors within each, we do not present the entire results, but instead the most important information from each model. We present the coefficient and significance of the minority gender predictor, the predictor of interest, and then provide the coefficient and significance of a comparison predictor — one of the control values of equal or higher significance and approximately equivalent strength. We provide the complete regression table for one model as an example in Appendix A. We highlight rows with significant results that align with past work in green, and those that disagree with past work in yellow. Roles S (safety officer), PD (project documenter), PM (Project Manager), and T (teamwork officer), shown in the comparison predictor column, describe roles in the project that students can take on.

We found very little evidence of gendered communication styles in our data. While being a minority gender was a significant predictor of using elaborate or supportive communication in an initial model, this relationship became insignificant when interactions between gender and controls were added. Here, we see some interactions become significant — some examples being minority genders are more likely to use elaborate communication when they are in a team with a high percentage of minority genders, and men are more likely to use supportive communication when asking a question. Some of the predicted individual measures of elaborate communication are significant, such as minority genders using more exclamation marks, and men using larger words, and we found significant support for men using more affective adjectives — which is opposite of what past work would predict. Within supportive communication, we found that minority genders were more likely to use pronouns. There were no gendered relationships within uncertain communication.

Most of the r^2 values for these models are considered low in regression analyses, although they are in line with previous linguistic studies. Savicki et al. [98] predicted the proportion of men in a group, and found that their linguistic characteristics only accounted for 0.025-0.03 of the variation.

Table 2. Summary of models used to answer the first research question. Green rows represent significant predictors in line with literature, yellow represents significant predictors that oppose literature. Baseline p values are presented but only $p < 0.0011$ are considered significant at the 0.05 level to correct for multiple tests. MG = Minority genders. PM, S, PD, T represent specific student roles in this course that are described in the text. Phase refers to stages in the course project, a proxy for time in the semester.

Dependent Variable	Interaction?	Minority Gender Effect	Comparison Predictor	r^2
Elaborate composite	No	$\beta = 0.030, p < 0.001$	team gender: $\beta = 0.151, p < 0.001$	0.262
Elaborate composite	Yes	$\beta = 0.048, p = 0.038$	MG X team breakdown: $\beta = 0.099, p < 0.001$	0.266
Absolute Vader sentiment	Yes	$\beta = 0.069, p = 0.285$	MG X role S: $\beta = 0.051, p < 0.001$	0.172
Absolute Flair sentiment	Yes	$\beta = -0.064, p = 0.034$	MG X ask reply: $\beta = 0.256, p < 0.001$	0.243
Affective adjectives	Yes	$\beta = -0.241, p = 0.001$	Men X 2018 $\beta = -0.008, p < 0.001$	0.001
Emoji count	Yes	$\beta = -0.104, p = 0.110$	men X question $\beta = 0.053, p < 0.001$	0.027
Emoticon count	Yes	$\beta = 0.014, p = 0.829$	men X role PD: $\beta = -0.130, p < 0.001$	0.213
Many punctuation	Yes	$\beta = 0.210, p = 0.003$	MG X 2018: $\beta = -0.101, p < 0.001$	0.004
Exclamation mark count	Yes	$\beta = 0.388, p < 0.001$	MG X team breakdown: $\beta = 0.361, p < 0.001$	0.200
Emotion	Yes	$\beta = 0.055, p = 0.437$	Men X question: $\beta = 0.027, p < 0.001$	0.013
Big Words†	Yes	$\beta = -0.262, p < 0.001$	MG X afternoon: $\beta = -0.033, p < 0.001$	0.090
Adjectives	Yes	$\beta = 0.020, p = 0.779$	Men X Phase 7: $\beta = -0.192, p < 0.001$	0.009
Vocabulary Richness†	Yes	$\beta = 0.078, p = 0.118$	Men X ask react: $\beta = -0.171, p < 0.001$	0.506
Uncertainty composite	No	$\beta = 0.001, p = 0.261$	question: $\beta : 0.022, p < 0.001$	0.093
Uncertainty composite	Yes	$\beta = 0.004, p = 0.832$	person mention: $\beta = -0.057, p < 0.001$	0.094
Filler	Yes	$\beta = -0.037, p = 0.594$	high Slack user: $\beta = 0.021, p < 0.001$	0.001
Cause	Yes	$\beta = 0.094, p = 0.182$	Men X ask react: $\beta = 0.230, p < 0.001$	0.024
Tentative	Yes	$\beta = -0.097, p = 0.168$	person mention: $\beta = -0.102, p < 0.001$	0.011
Negate	Yes	$\beta = -0.164, p = 0.021$	high Slack user: $\beta = 0.017, p < 0.001$	0.005
Discrepancy	Yes	$\beta = 0.096, p = 0.175$	Men X role PM: $\beta = 0.051, p < 0.001$	0.013
Insight	Yes	$\beta = -0.088, p = 0.211$	question: $\beta = 0.210, p < 0.001$	0.015
Clout†	Yes	$\beta = -0.043, p = 0.530$	MG X team breakdown: $\beta = 0.192, p < 0.001$	0.079
Need†	Yes	$\beta = -0.108, p = 0.127$	role T: $\beta = -0.034, p < 0.001$	0.005
All or None†	Yes	$\beta = -0.122, p = 0.084$	Men X role PM: $\beta = 0.049, p < 0.001$	0.007
Certitude†	Yes	$\beta = -0.178, p = 0.013$	channel mention: $\beta = -0.067, p < 0.001$	0.002
Intense Adverbs	Yes	$\beta = -0.090, p = 0.165$	Men X ask react: $\beta = 0.238, p < 0.001$	0.164
Uncertainty	Yes	$\beta = 0.071, p = 0.310$	MG X message length: $\beta = 0.001, p < 0.001$	0.031
Hedges	Yes	$\beta = -0.070, p = 0.265$	MG X message length: $\beta = -0.002, p < 0.001$	0.225
Apologies	Yes	$\beta = -0.105, p = 0.138$	Men X ask reply: $\beta = 0.358, p < 0.001$	0.007
Supportive composite	No	$\beta = 0.023, p < 0.001$	ask react: $\beta = 0.063, p < 0.001$	0.005
Supportive composite	Yes	$\beta = -0.007, p = 0.743$	Men X question: $\beta = 0.014, p < 0.001$	0.005
Assent	Yes	$\beta = -0.025, p = 0.723$	Men X phase 1: $\beta = 0.083, p < 0.001$	0.019
Agreement Words	Yes	$\beta = -0.087, p = 0.207$	Men X role S: $\beta = 0.050, p < 0.001$	0.049
Disagreement Words†	Yes	$\beta = -0.027, p = 0.706$	channel mention: $\beta = -0.088, p < 0.001$	0.014
Tone	Yes	$\beta = -0.083, p = 0.239$	MG X message length: $\beta = 0.001, p < 0.001$	0.018
Prosocial Behaviour	Yes	$\beta = 0.001, p = 0.993$	Men X question: $\beta = 0.035, p < 0.001$	0.007
Politeness	Yes	$\beta = -0.000, p = 0.999$	Men X 2017: $\beta = -0.075, p < 0.001$	0.006
Cognition	Yes	$\beta = -0.116, p = 0.099$	Men X role PM: $\beta = 0.050, p < 0.001$	0.014
Pronouns	Yes	$\beta = 0.251, p < 0.001$	Men X role PM: $\beta = 0.049, p < 0.001$	0.018
Differentiation	Yes	$\beta = 0.099, p = 0.162$	person mention: $\beta = -0.131, p < 0.001$	0.009
Swear†	Yes	$\beta = -0.037, p = 0.604$	Men X phase 1: $\beta = 0.053, p < 0.001$	0.002
Determiners†	Yes	$\beta = 0.057, p = 0.415$	MG X phase 1: $\beta = 0.130, p < 0.001$	0.027
Quantities†	Yes	$\beta = 0.031, p = 0.657$	Men X question: $\beta = -0.035, p < 0.001$	0.011
Impersonal Pronouns†	Yes	$\beta = 0.087, p = 0.214$	Men X role T: $\beta = 0.050, p < 0.001$	0.024
Social Words	Yes	$\beta = 0.068, p = 0.333$	Men X question: $\beta = 0.031, p < 0.001$	0.013
Affiliation	Yes	$\beta = -0.079, p = 0.264$	MG X team breakdown: $\beta = 0.296, p < 0.001$	0.015
n=334,859 for all models.				

Nonetheless, this still suggests that communication styles may be better predicted by characteristics that we don't capture here.

Table 3. Selected results for the second research question. Model 1 represents just gender and controls, Model 2 adds in communication characteristics, and Model 3 adds interaction effects between gender and communication characteristics. MG = minority gender, EC = elaborate communication, UC = uncertain communication, SC = supportive communication. Green highlights represent significant results. p values are Bonferroni adjusted for multiple tests in Models 2 and 3 (adjusted for four tests in Model 2 and seven tests in Model 3).

Dependent Variable	Model	Gender	Characteristics	Interactions	pseudo r^2
React	1	$\beta = 0.059, p < 0.001$	-	-	0.054
React	2	$\beta = 0.040, p < 0.001$	EC: $\beta = 0.434, p < 0.001$ UC: $\beta = -0.156, p < 0.001$ SC: $\beta = 0.156, p < 0.001$	-	0.059
React	3	$\beta = 0.0389, p < 0.01$	EC: $\beta = 0.399, p < 0.001$ UC: $\beta = -0.152, p < 0.001$ SC: $\beta = 0.220, p < 0.001$	Gender X EC: $\beta = 0.058, p = 0.1394$ Gender X UC: $\beta = -0.005, p = 1.00$ Gender X SC: $\beta = -0.111, p < 0.01$	0.059
Reply	1	$\beta = -0.012, p = 0.127$	-	-	0.097
Reply	2	$\beta = -0.023, p = 0.515$	EC: $\beta = 0.006, p = 1.00$ UC: $\beta = -0.034, p = 0.795$ SC: $\beta = -0.014, p = 1.00$	-	0.097
Reply	3	$\beta = -0.024, p = 0.7983$	EC: $\beta = -0.007, p = 1.00$ UC: $\beta = -0.040, p = 1.00$ SC: $\beta = 0.026, p = 1.00$	Gender X EC: $\beta = 0.019, p = 1.00$ Gender X UC: $\beta = 0.010, p = 1.00$ Gender X SC: $\beta = -0.070, p = 1.00$	0.097
Engaged with - MG	1	$\beta = 0.488, p < 0.001$	-	-	0.023
Engaged with - MG	2	$\beta = 0.487, p < 0.001$	EC: $\beta = 0.008, p = 1.00$ UC: $\beta = 0.055, p < 0.01$ SC: $\beta = 0.044, p < 0.05$	-	0.023
Engaged with - MG	3	$\beta = 0.481, p < 0.001$	EC: $\beta = 0.148, p < 0.001$ UC: $\beta = -0.030, p = 1.00$ SC: $\beta = 0.123, p < 0.001$	Gender X EC: $\beta = -0.219, p < 0.001$ Gender X UC: $\beta = 0.139, p < 0.001$ Gender X SC: $\beta = -0.146, p < 0.001$	0.024

n=189,191 for replies analysis; n=334,859 for reacts analysis; n=197,575 for engaged with - MG analysis

4.2 RQ2: Engagement Dynamics

The answers to our second research question — how these gendered styles correlate with engagement on ECPs — are shown in Table 3. Due to the significant number of controls present in these models, here we present only the coefficients of interest: gender, communication characteristics, and their interactions, as well as the model fit. See Appendix B for an example of the full regression table for one model. We found that being a minority gender was a significantly *positive* predictor of having your message reacted to, as was using elaborate and supportive communication characteristics. Using uncertain communication characteristics, on the other hand, was a significant negative predictor of having your message reacted to. Being a minority gender and using supportive communication meant a message was less likely to be reacted to. There were no significant relationships when predicting whether a message would be replied to.

In the final analysis, we used gender, controls, and communication characteristics to predict the gender of the person who replied or reacted to a message. Being a minority gender meant that your message was more likely to be engaged with by a minority gender, as does using elaborate and supportive communication. Notably, being a minority gender and sending uncertain communication made it more likely for the message to be engaged with by a minority gender — but less likely if the communication was elaborate or supportive. The pseudo r^2 values in this analysis are also low, though they are similar to the values reported in Pierson et al.'s prediction of the number of recommendations a comment would receive ($r^2 < 0.1$) on the New York Times comment section [91].

5 DISCUSSION

Here we compare our gendered language findings to past work and propose potential explanations for our findings. We discuss the implications this study has for both the CSCW community, the study of gendered linguistics, and the design of ECPs, and we describe the limitations of this work.

5.1 Gendered Language

In this work, we investigated whether traditionally gendered communication styles, which have been found in various contexts in the past [54, 98], can be found on modern Enterprise Communication Platforms. We did not find strong evidence for minority genders' use of elaborate, uncertain, or supportive communication. The only significant relationships which confirm past findings were minority genders' use of exclamation marks and pronouns, and men's use of large words. As many of the measures used in our study came from the commonly used Linguistic Inquiry and Word Count (LIWC) dictionary, we can directly compare our results to past work referencing the same dictionary. For example, Schwartz et al. [100] used an open vocabulary approach applied to Facebook status updates to understand the relationship between language, gender, and age, also comparing their results to LIWC. They found support for some elements of our definition of supportive communication: women used more personal pronouns and social references, while men use more impersonal pronouns, articles, quantifiers, and swear words. Similar to our findings, they found no relationship between gender and elements of uncertainty. Overall, they identified many more significant differences between men's and women's language than we uncovered, which could be explained by analyzing a less formal and less synchronous setting, as both formality and synchronicity have been shown to influence language use in past work [39, 51]. Further, they analyzed over 15 million status updates, and while our dataset is sizable in the context of ECPs [7, 25], we are limited in our ability to uncover small effect sizes.

Newman et al. aimed to identify generalizable gendered language patterns by using LIWC to analyze a large sample of texts from global research labs, as well as books, poems, and other art forms [87]. They identified gendered differences in almost all of the LIWC categories available at the time, including those tested in our analysis. They were able to discern that gendered differences are larger when there are fewer constraints on language use — further suggesting that we might see fewer significant relationships in a classroom setting, where we would expect team norms, expectations of technical and professional communication, and the presence of teaching staff all to impose some form of constraint.

In perhaps the most similar context to ours, Savicki et al. [98] qualitatively analyzed the content of discussion boards where small groups worked to complete a task. Of the 13 categories of communication they coded, they found significant differences in only four: men used more facts and action words, and women were more likely to self-disclose and try to prevent tension. Self-disclosure is often categorized by personal pronoun use, which we also found to be associated with minority genders. The fewer significant differences found by Savicki et al. [98] when compared to other past work may suggest that gendered language is less prevalent when the goal of communication is to complete a collective task.

While our more formal, task-focused context might explain the lack of evidence for gendered communication styles, another possible explanation is the tool being studied. Much of the past work we drew on to form our predictions investigated communication on now-outdated platforms, like listservs [50]. It is important that we update our understanding of social theories as both the tools and contexts they are used in change. ECPs allow for near-synchronous collaboration, unlike discussion boards and listservs, and when used in a workplace or classroom setting, it is unlikely that one would post anonymously. Further, more user information is often visible on these

platforms — Slack specifically allows users to upload a photo, title, status, and contact information — this transparency may make gender more apparent, or, may instead bring the focus to other aspects of one's identity such as their role on the team.

Another potential explanation for our findings could be the gender diversity in this class. Communication Accommodation Theory describes how individuals adapt their communication styles in response to those around them, often used to signal identity through membership or distance from a group [29]. Since the teams we study contain roughly an equal number of men and women, potentially all genders have adapted their language to match those around them, resulting in a "genderless" communication style. Complicating this interpretation is the broader context of Mechanical Engineering that these students exist within. While this specific course is gender diverse, the students are likely exposed to male-dominated environments in other courses, internships, or within their peer groups. This could lead to some women and minority genders taking on masculine communication characteristics, either unconsciously, or consciously, in order to fit in. We show some evidence for this effect in our work — because we control for the gender breakdown of the team, we can see instances where minority genders' communication changes based on the breakdown of the team. For instance, minority genders use more elaborate communication, exclamation marks, and affiliation terms (all traditionally feminine characteristics) when the percentage of minority genders in the group is higher.

Lastly, our models controlled for a number of factors regarding the message author and the message itself, allowing us to uncover significant interaction effects. We see that being a minority gender is a significant predictor of both elaborate and supportive communication initially, but this effect diminishes when interactions, such as gender and role on the team, are added. This suggests that the relationship between gender and communication may be more complex and depends on the characteristics of each unique context.

Regardless of the cause of our findings, this work demonstrates a rather stark departure from the long-held beliefs of gendered communication styles, encouraging researchers to revisit these ideas in new contexts and tools.

5.2 Unequal Engagement

The second aim of this work was to investigate whether gendered power dynamics exist on ECPs, and whether they are related to gendered communication styles. Herring [52] described how our understanding of "holding the floor," or having the power in a conversation, is different when we communicate virtually. Since a message can go unread and ignored, one can only hold power if their conversation is acknowledged or continued. Modern ECPs have features that allow one to directly engage with a message, such as reactions or replies. We found that minority genders' messages were more likely to be reacted to — contrary to what would be predicted from past work [52, 98]. We did not find a relationship between gender, communication style, and threaded replies; but this finding could be influenced by a limitation of our measure of replies. While Slack enables threaded replies, users may not be disciplined in their use of this feature, instead replying by sending a new message — and these replies would not be captured in our analysis. Manually matching replies by looking for a reference to the past message, as done in past work [52], may yield different results.

Further, we found that elaborate and supportive communication was more likely to be reacted to. Elaborate communication includes emotion; emotional messages might imply to the group that the message author is excited or passionate about the content, or that the message is urgent, both of which could prompt them to acknowledge the message with a reaction. Supportive communication is characterized by agreement with and discussion about other people — referencing others or their ideas understandably would prompt acknowledgement from those team members. Uncertain communication, characterized by tentative language and hedgers, was correlated with fewer

reactions. Reactions are often used as a "virtual nod" — a quick way to signal agreement [106]. Perhaps team members are hesitant to agree with an idea where the message author seems unsure, or, perhaps these uncertain messages prompt a response in the form of a detailed reply instead of a quick reaction. Similarly, it could be that these uncertain messages represent complex roadblocks that need to be resolved in order to move forward, where team members lack the motivation or time to respond, or would prefer to discuss in person. When looking at the interaction between gender and communication, we found that while in general supportive communication is more likely to be reacted to, it is less likely to be reacted to when sent by a minority gender. Within supportive communication, minority genders only differed in their use of pronouns — so perhaps a greater use of pronouns leads to this discrepancy. A high concentration of pronouns describes conversations about people, compared to things [89]; thus these messages may be less relevant to the product design, and receive less engagement in this class context. Conversely, perhaps these individuals displaying traditionally feminine communication characteristics means their contributions are taken less seriously. Acquiring a deeper understanding of how users decide to use ECP features can help to illuminate the mechanisms behind these findings.

Our finding that minority genders are more likely to have their messages reacted to contradicts past work, such as women's reviews receiving fewer likes than men's [44], men receiving more responses than women on discussion boards [52], and groups dominated by women having fewer responses overall [98]. Reactions in this context are similar to likes in [44] but have distinctly different meanings and communicative goals than replies. Which points to the question: what is the difference between replies and reactions when considering who has power on ECPs? By the definition in Herring's past work [52], both replies and reactions represent message acknowledgement (contrasting with a message being unread and ignored), suggesting they may be a measure of power. However, reactions might signal the end of the conversation — maybe the team member agrees with the idea but does not want to discuss it further, or does not have any feedback to provide. Thus, while reactions signal acknowledgement, on their own, they do not signal whether a conversation is continued — only replies signal this. Therefore, more work is needed to understand how replies are distributed across genders in order to determine who has control of the conversation.

While holding the floor is one measure of conversational control, other work has simply measured who dominates the platform. While some studies found that men post more often [48, 103], most found that women send more messages [10, 13, 52, 114]. The findings were more mixed in terms of message length, with some finding that women write longer messages [79, 80, 96], and others finding the opposite [20, 51, 110]. We found that minority genders send more messages, more replies, and more reactions, though there was no difference in message length. Based on past work, this in itself may be evidence of minority genders holding power in this setting. Alternatively, this could be interpreted as these individuals carrying the burden of keeping the communication going. This could be because women are often stereotyped as being more social and better communicators than men [104], which can lead to their promotion from technical to managerial roles [22]. This suggests an open research direction: do women's higher participation in online group settings suggest they have control of the conversation, or that they shoulder the burden of keeping it going?

Lastly, we investigated which features of a message made it more likely to be engaged with by a minority gender. While Thelwall et al. found no relationship between the gender of the message author and receiver when studying emotional communication [113], we found significant relationships between message author and receiver gender. We found that minority genders were more likely to engage with messages from other minority genders. However, we found that minority genders using elaborate or supportive communication were less likely to be engaged with by other minority genders as opposed to men, but minority genders using uncertain communication were more likely to be engaged with by another minority gender. This might suggest that minority

genders are more sensitive to uncertain communication and thus engage with the message to provide support or feedback.

These findings on the relationship between communication style and message engagement have implications for computer-supported cooperative work. While gender might not be correlated with communication style, we've shown that the communication styles are correlated with message engagement. This suggests that messages containing new ideas, critical updates, or time-sensitive questions may be ignored if they are communicated in a certain style.

5.3 Implications for the Research and Use of Computer-Supported Collaboration

This work has significant implications for the further study and use of ECPs. We found that the amount of engagement a message receives is related to the author's gender and the communication style used. Engagement on these platforms, or a lack of engagement, can influence participation more broadly — women are less likely to continue posting on a discussion board if they do not receive a reply [51]. In terms of reactions or likes, past studies of Facebook behaviour found that not receiving enough likes on a post can make one feel bad [101], and in a workplace setting, individuals reported liking comments to encourage further participation [41]. This suggests that disparities in online engagement — either caused by gender or communication style — may lead to reduced participation. Diverse contributions are important for problem-solving [23, 56, 75] and productivity [118], suggesting that this reduced participation can put teams using ECPs at a disadvantage. However, the knowledge-sharing and trust-building benefits of ECP usage [19] suggest that we should design more inclusive ECPs, as opposed to abandoning them altogether.

Further, our focus on message author gender, group gender composition, and interactions between genders allowed us to identify how individuals change their communication style based on who they are communicating with. Much of the past work on gendered linguistics found that those in the minority in a group adapted their communication style to match the majority [49, 114, 115]. While the teams studied in this work averaged a 50/50 minority gender/men split, the individual variation across teams allowed us to identify how minority genders' communication changed when they made up the majority in their team — for example, by using more exclamation marks. While past work has shown that token minorities in a group display fewer gendered communication characteristics [49], our sample allowed us to identify specific elements of communication that change. Further, by analyzing the gender of both the message author and receiver (who engaged with the message), we were able to identify potential communication norms in these teams. For example, minority genders were more likely to react to a message if it also was written by a minority gender — perhaps suggesting that they use these types of interactions with individuals who they know value them. Broadly, we would like to encourage the CSCW community to continue to consider gender, gendered interactions, and group gender composition in future work.

Our paper adds to the growing study of instant messaging and group chat dynamics at CSCW [70, 71, 92, 102], filling an understudied niche related to gendered communication and power. Our analysis of gendered communication is similar to that of Hemphill et al.'s study of gendered language on the Internet Movie Database (IMDB) [44]. We echo their findings that women use more pronouns and fewer big words, but we do not find evidence for women's extensive use of hedging and limited vocabulary. Thus, we show that some linguistic characteristics are prevalent across different virtual communication types, but some are different, suggesting the platform has an effect; for instance, IMDB differs from Slack in terms of its context (movies), synchronicity (asynchronous), and ability to be anonymous, which highlights features of ECPs that may contribute to the lack of traditional gendered language styles we observed. Further, Pierson et al. studied the interaction that comments received on the New York Times website [91]. Similar to our finding that minority genders receive more reactions, they found that comments written by women were more likely to

be recommended. They also found that women were more likely to comment on articles written by women, similar to our findings of reaction patterns. These similar findings from studies of very different technology contexts suggest that some of these gendered dynamics are generalizable across platforms. We call for the continued investigation of these platforms, and particularly their use in enterprise or professional settings.

5.4 Implications for Gendered Linguistics Research

This study provides initial evidence that the gendered communication styles, long agreed upon in the linguistic community, may need to be revisited in light of new communication tools and the continuing evolution of our understanding of gender and its construction. While our study of a single context does not alone refute the abundant existing evidence for these styles [51, 53, 98], it does provide further support for the idea that language styles depend largely on context [8, 36, 45, 64, 114, 115]. We contribute findings from a context that is unique in three ways: we study modern communication (2016-2021), happening on emerging and understudied formal communication platforms, from individuals in gender-diverse teams existing in a broader non-diverse field. We encourage the linguistic community to continue revisiting past findings in modern contexts so that we can disentangle the characteristics that influence changes in communication style.

Another reason why our findings might differ from some of the initial studies in this area is due to the quantitative method we employ. Our use of linguistic dictionaries classifies language styles on the basis of the inclusion of a set of terms, compared to most of the older work in this area, which qualitatively analyzed virtual communication [80, 96, 98]. The use of such an analysis method allows for the large-scale of messages (335,000) and participants (845) analyzed in this study. These quantitative dictionaries are unable to identify more complex characteristics of linguistic styles, such as conflict [120], and may miss instances of a communication style that a researcher would identify via a more qualitative approach. Yet to fully explore the volume of data provided by modern virtual communication platforms — and analyzed in this study — requires automated measures. We imagine future work in this field that combines the benefits of both qualitative and quantitative analysis.

5.5 Enterprise Communication Platform Design Implications

We further suggest design implications for ECPs to implement our findings. Fortunately, the flexibility of ECPs offers easy avenues for implementing design changes, due to the ability to design third-party add-in tools that users can download, for example, from the Slack app store [7]. For instance, our peers in the CSCW community can design plug-in tools that can identify language patterns, such as uncertain, emotional, or supportive language, in real-time, and prompt users to re-word their message, similar to Grammarly's identification and correction of passive language[8]. Based on our findings that messages containing uncertain communication are less likely to be engaged with, the intervention could look like an automated message that appears in the ECP message feed (though visible only to the message sender) suggesting an edit to their message. This could also be designed to edit messages in real-time, as you type, a functionality already implemented in Microsoft Teams[9]. Such an intervention requires further investigation — we should not jump to the conclusion that all users should adjust their communication to match the majority in a group. Alternatively, instead of requesting some users to adapt their language in order to capture attention, these plug-ins could instead identify messages that have not received any

[7] https://slack.com/apps

[8] https://www.grammarly.com/passive-voice-checker

[9] https://support.microsoft.com/en-gb/office/use-editor-text-predictions-to-type-faster-in-teams-e5534601-380a-4b8a-ad95-ea2a21b10b75

engagement after a certain period of time and push these to users again. Further, before intervening in team communication, perhaps we should begin by building tools that simply monitor the communication on these platforms. For managers, educators, or team leaders who are concerned about the inclusivity of their online environment, add-in tools could be downloaded that track communication and engagement patterns over time, and provide personalized reports to each individual or team leader. Even a single automated message, such as "67% of the messages you engaged with this month were sent by men", may be enough to prompt users to be conscious of their actions and make efforts to be more inclusive. We hope to inspire CSCW designers to consider the inclusivity of the online spaces they create.

5.6 Limitations

One limitation of this work is our choice of a closed-dictionary, quantitative method. Utilizing existing language dictionaries allowed us to uncover aspects of gendered language that were consistent across 46 student teams and six years. While it would be infeasible to hand-code this volume of data, some scholars have criticized these automated measures of stylistic features [54], indicating that these dictionaries are not perfectly reliable. This is a necessary trade-off in current CSCW research—digital technologies provide volumes of data that can facilitate specialized research, though they often require automated methods for analysis. Further, these linguistic dictionaries may themselves be based on outdated or context-specific studies. In fact, by using a closed-dictionary approach, we limit our ability to uncover new gendered language styles. Our aim here was to look for initial evidence of previously identified gendered styles on a new platform; the limited significant relationships suggest that these language patterns may have changed over time or differ by medium, and open-dictionary approaches can be used to identify current patterns.

The context of our work is important to consider when interpreting our results. Our dataset contains messages from numerous individuals and years, thus broadening our findings from being unique to a small number of individuals or a specific period of time. However, studying one class context limits our ability to disentangle the potential causes behind the patterns we see. The lack of gendered communication patterns may be related to the formality of a classroom setting, the ECP itself, or the traditionally masculine environment.

Further, there are some limitations of our data collection method. First, we remove approximately 6% of the messages in our dataset from individuals who did not consent, or did not provide their gender. While this is a small percentage, we are unable to completely determine if the engagement or language patterns within this group systematically differ from the larger group, due to restrictions in the ethics protocol. However, we do show that the gender breakdown in our sample generally matches the gender breakdown of the major as a whole, suggesting there are no gendered patterns in consent practices for our study. As a further limitation, we only collect messages sent in public Slack channels. While Slack also allows users to communicate via direct messages, this is not captured in this analysis. Thus, these findings demonstrate communication patterns in public messages on ECPs.

Lastly, we are limited by the characteristics of our participants. The small number of messages from individuals who identify outside of the gender binary limits our ability to characterize linguistic patterns from this group. We choose to combine those who identify as women with these individuals under the category of "minority genders" as both are typically in the minority in our context of Mechanical Engineering. To our knowledge, there is no past work that analyzed the gendered linguistics for those identifying outside of the gender binary, thus it is possible that their linguistic patterns differ greatly from women's, which would be obscured in our analysis. As we update our understanding of gendered language by studying modern communication tools, we should take advantage of the volume of data available, and prioritize the study of gender-diverse groups.

Lastly, the data used in this work comes from students in a classroom setting. While the fourth-year project aims to mimic a real word design project as closely as possible, students' language use may differ from enterprise or professional settings due to the power dynamics between students and instructors or the existing interpersonal relationships between team members.

6 FUTURE WORK

While we have suggested areas for future work and open research questions throughout section 5, we summarize these concisely here. The work in this paper used a closed-vocabulary approach, which relies on a priori word categorization. While this categorization builds on decades of research, the analysis can only be robust as the dictionaries used. Closed-vocabulary approaches represent a replicable method that can be used to study and compare new contexts to old, but future work can use open-vocabulary approaches, that define linguistic patterns based on the data [100], to uncover new patterns. Further, we discussed the limitations and advantages of using quantitative methods in this study; researchers can address these limitations by using qualitative analysis applied to a subset of data to verify and update the quantitative methods used.

We encourage the continuation of this work with data collected in diverse settings. Conducting these gendered analyses on data collected in traditionally masculine, traditionally feminine, and gender-diverse environments will allow for the identification of linguistic styles that change based on group gender composition, as opposed to other elements of the setting. While we begin the study of gendered interactions by predicting engagement from minority genders, we leave the investigation of gender interaction and linguistic patterns to future work. For instance, future research can analyze whether minority genders use different linguistic characteristics when speaking with other minority genders. This analysis would require analyzing targeted communication (such as at-mentions or direct messages).

Further, studying data across various industries, tasks, and communication platforms will allow for the disentanglement of the mechanisms behind our findings. As our findings differed significantly from much of the work conducted in the 1990s, an interesting line of inquiry would be to investigate how age or generational differences correlate with linguistic style. Last but not least, future work should analyze gendered communication styles more broadly, beyond comparing only women and men.

7 CONCLUSIONS

In this work, we conducted a quantitative investigation into the gendered language styles on Enterprise Communication Platforms. Using Slack messages collected over six years of a product design capstone course — representing 845 users and 335,000 individual messages — we used linguistic dictionaries to identify characteristics of elaborate, uncertain, and supportive communication styles from past work. Then, we used these stylistic measures, combined with gender, to predict whether a message would receive engagement.

So, when it comes to communication, are we equal online? We show that the answer is complex. While we found limited evidence for the relationship between gender and traditionally gendered communication styles in our dataset, we identified that both gender and communication style correlate with message engagement. Messages written by minority genders or containing elaborate and supportive communication styles were more likely to be reacted to, but when minority genders used supportive communication styles, they received fewer engagements. Further, uncertain communication was engaged with less frequently, unless it was both written, and engaged with, by a minority gender. In summary, we found that the power dynamics on these platforms depend both on gender and communication style.

We contribute the first investigation of gendered communication styles and power dynamics on Enterprise Communication Platforms. Our findings, and their departure from past work, suggest open research areas for future work. We encourage the further study of gendered communication and power dynamics, and how they emerge in various settings and on different communication platforms.

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A RQ1 REGRESSION TABLE

Table 4. Full regression results for the Elaborate composite with interaction effects. MG = minority gender. Baseline p values are presented but only $p < 0.0011$ are considered significant at the 0.05 level to correct for multiple tests; those such rows are highlighted in yellow. Omitted = omitted due to multicollinearity. N = 334,859

Variable	Coef.	t	p	Variable	Coef.	t	p
Minority Gender	0.048	2.07	0.038	MG X Safety Officer			
Team Gender Composition	0.064	4.60	0.000	0 1	0.017	3.63	0.000
Staff	0.089	4.12	0.000	1 0	omitted		
Role - Project Manager	0.019	7.08	0.000	1 1	omitted		
Role - Teamwork	0.0.36	12.43	0.000	MG X Team Documenter			
Role - Financial	0.011	3.59	0.000	0 1	-0.058	-7.46	0.000
Role - Information Officer	0.009	2.90	0.004	1 0	omitted		
Role - Tool Officer	0.021	5.95	0.000	1 1	omitted		
Role - Safety Officer	-0.009	-2.72	0.007	MG X Slack Officer			
Role - Project Documenter	0.024	6.84	0.000	0 1	0.007	1.43	0.153
Role - Slack Officer	-0.007	-2.23	0.026	1 0	omitted		
High Slack User	-0.000	-0.25	0.803	1 1	omitted		
Year	-0.017	-4.89	0.000	MG X Message Length	0.001	24.97	0.000
Time of Day - Evening	-0.000	-0.08	0.934	MG X Afternoon	-0.001	-0.45	0.654
Time of Day - Morning	0.009	3.48	0.001	MG X Evening	0.002	0.61	0.545
Time of Day - Night	0.009	3.81	0.000	MG X Morning	0.003	0.85	0.397
Proximity to Deadline	0.000	5.35	0.000	MG X Proximity to Deadline	0.000	2.77	0.006
Phase of Design Process	-0.003	-1.46	0.144	MG X Phase of Design Process			
Person Mention	-0.133	-51.52	0.000	0 1	-0.001	-0.27	0.789
Channel Mention	0.191	43.09	0.000	0 2	0.003	0.53	0.594

Table 4 continued from previous page

Variable	Coefficient	t	p	Variable	Coefficient	t	p
Ask for Reaction	0.286	27.37	0.000	0 3	0.003	0.31	0.953
Ask for Reply	0.060	3.74	0.000	0 4	-0.005	-0.51	0.612
Question	-0.065	-39.72	0.000	0 5	-0.000	-0.01	0.988
MG X Question				0 6	0.008	0.56	0.574
0 1	0.023	8.90	0.000	1 1	-0.007	-0.68	0.495
1 0	omitted			1 2	-0.007	-0.80	0.424
1 1	omitted			1 3	-0.004	-0.64	0.523
MG X Gender Breakdown	0.099	5.47	0.000	1 4	-0.009	-2.02	0.044
MG X Staff				1 5	omitted		
0 1	-0.057	-2.48	0.013	1 6	omitted		
1 0	omitted			MG X Person Mention			
1 1	omitted			0 1	-0.006	-1.37	0.171
MG X Project Manager				1 0	omitted		
0 1	0.002	0.61	0.545	1 1	omitted		
1 0	omitted			MG X Channel Mention			
1 1	omitted			0 1	-0.071	-9.75	0.000
MG X Teamwork Officer				1 0	omitted		
0 1	-0.013	-2.82	0.005	1 1	omitted		
1 0	omitted			MG x Ask for Reaction			
1 1	omitted			0 1	-0.125	-6.57	0.000
MG X Financial Officer				1 0	omitted		
0 1	-0.018	-3.65	0.000	1 1	omitted		
1 0	omitted			MG X Ask for Reply			
1 1	omitted			0 1	0.031	1.16	0.246
MG X Information Officer				1 0	omitted		
0 1	-0.016	-3.41	0.001	1 1	omitted		
1 0	omitted			MG X Year			
1 1	omitted			0 2016	omitted		
MG X Tool Officer				0 2017	-0.010	-2.02	0.043
0 1	-0.008	-1.52	0.129	0 2018	0.021	2.77	0.006
1 0	omitted			0 2019	0.041	3.83	0.000
1 1	omitted			0 2020	0.103	7.12	0.000
Cons	33.914	4.87	0.000	0 2021	0.077	4.38	0.000
				1 2016	-0.081	-4.89	0.000
				1 2017	-0.078	-5.99	0.000
				1 2018	-0.065	-6.89	0.000
				1 2019	-0.042	-6.67	0.000
				1 2020	omitted		
r^2	0.267			1 2020	omitted		

B RQ2 REGRESSION TABLE

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Table 5. Full regression table for the prediction reactions with communication characteristics and the interaction between characteristics and gender. MG = Minority Gender. Non-adjusted p values are shown in the p column, and for the variables of interest, Bonferroni-adjusted p values are shown in the last column. N=334,859

Variable	**Coefficient**	**Z**	**p**	Chi^2	**Bonferroni-corrected p**
Minority Gender	0.039	3.52	0.000	12.40	0.003
Gender Breakdown	1.164	16.82	0.000		
Staff	0.244	3.83	0.000		
Role - Project Manager	0.093	5.11	0.000		
Role - Teamwork Officer	0.109	5.58	0.000		
Role - Financial Officer	0.134	6.62	0.000		
Role - Information Officer	0.076	3.70	0.000		
Role - Tool Officer	0.007	0.33	0.744		
Role - Safety Officer	0.023	1.08	0.278		
Role - Project Documentor	-0.044	-1.78	0.075		
Role - Slack Officer	0.114	5.17	0.000		
High Slack User	-0.144	-12.69	0.000		
Year	0.244	73.92	0.000		
Length of Message	0.010	41.09	0.000		
Time of Day - Evening	0.012	0.90	0.371		
Time of Day - Morning	0.037	2.47	0.014		
Time of Day- Night	0.080	5.91	0.000		
Proximity to Deadline	0.000	14.44	0.000		
Question	-0.429	-35.87	0.000		
Phase of Design Process	0.017	6.64	0.000		
Person Mention	-0.036	-1.88	0.060		
Channel Mention	0.416	15.23	0.000		
Ask for a Reaction	1.983	0.062	0.000		
Ask for a Reply	-0.087	-0.87	0.383		
Elaborate Composite	0.399	18.96	0.000	359.45	0.000
Supportive Composite	0.220	8.97	0.000	80.46	0.000
Certainty Composite	-0.152	-5.44	0.000	29.63	0.000
MG X Elaborate	0.056	2.33	0.020	5.44	0.138
MG X Supportive	-0.112	-3.45	0.001	11.93	0.004
MG X Certainty	-0.006	-0.15	0.881	0.02	1.000
cons	-494.994	-74.34	0.000		
pseudo r^2	**0.059**				