LibRA: On LinkedIn based Role Ambiguity and Its Relationship with Wellbeing and Job Performance

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Job roles serve as a boundary between an employee and an organization, and are often considered building blocks in understanding the behavior and functioning of organizational systems. However, a lack of clarity about one's role, that is, one's work responsibilities and degree of authority, can lead to absenteeism, turnover, dissatisfaction, stress, and lower workplace performance. This paper proposes a methodology to quantitatively estimate role ambiguity via unobtrusively gathered data from LinkedIn, shared voluntarily by a cohort of information workers spanning multiple organizations. After successfully validating this LinkedIn based measure of Role Ambiguity, or `LibRA` against a state-of-the-art gold standard, drawing upon theories in organizational psychology, we examine the efficacy and convergent validity of `LibRA` in explaining established relationships of role ambiguity with wellbeing and performance measures of individuals. We find that greater `LibRA` is associated with depleted wellbeing, such as increased heart rate, increased arousal, decreased sleep, and higher stress. In addition, greater `LibRA` is associated with lower job performance such as decreased organizational citizenship behavior and decreased individual task performance. We discuss how `LibRA` can help fill gaps in state-of-the-art assessments of role ambiguity, and the potential of this measure in building novel technology-mediated strategies to combat role ambiguity in organizations.

CCS Concepts: • **Human-centered computing** → *Empirical studies in collaborative and social computing*; *Social media*; • **Applied computing** → *Psychology*.

Additional Key Words and Phrases: LinkedIn; role ambiguity; social media; wellbeing; passive sensing; job performance; productivity; stress

ACM Reference Format:
Koustuv Saha, Manikanta D. Reddy, Stephen M. Mattingly, Edward Moskal, Anusha Sirigiri, and Munmun De Choudhury. 2019. LibRA: On LinkedIn based Role Ambiguity and Its Relationship with Wellbeing and Job Performance. *Proc. ACM Hum.-Comput. Interact.* 3, CSCW, Article 137 (November 2019), 30 pages. https://doi.org/10.1145/3359239

1 INTRODUCTION

Employee job satisfaction is of prime interest to both individuals as well as organizations. The complexities related to an individual's job role, or the *expectations applied to an individual within and beyond an organization's boundaries* can impact their job satisfaction [153]. In fact, any sort of

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2573-0142/2019/11-ART137 $15.00
https://doi.org/10.1145/3359239

discrepancy between *what* an employer expects and *what* an employee does at the workplace can impact wellbeing and performance, as employees can find themselves pulled in various directions as they try to respond to the many statuses they hold. According to the "Role Theory", role conflict, role ambiguity, and role overload are three aspects of job role that contribute to workplace stress, or the stress that arises if the demands of an individual's roles and responsibilities exceed their capacity and capability to cope [79, 112]. Among the role constructs, role ambiguity has been considered to be the most significant one, and it is also the focus of the current paper [79].

Role ambiguity is broadly considered to include uncertainties about role definition, expectations, responsibilities, tasks, and behaviors involved in one or more facets of the task environment [72, 79, 127]. Role ambiguity has both objective and subjective components — Objective role ambiguity refers to external conditions in the individual's workplace environment, whereas subjective role ambiguity relates to the amount of ambiguity that the individual perceives in their workplace owing to the information gap that they face [79]. Further, role ambiguity leads to consequences related to dissatisfaction, distrust, lack of loyalty, turnover, absenteeism, low performance, anxiety-stress, and increased heart rate [153]. There is sufficient evidence demonstrating how role ambiguity negatively affects one's organizational life in terms of their physiological, behavioral, psychological, and performance related measures [78, 127].

Traditionally, role ambiguity is measured using survey instruments that record employee responses to their perceived clarity of assigned tasks, expectations on the job, expectations of peers, and if these peers explicitly mention their expectations from the focal employee [117]. In particular, these methods not only suffer from subjective biases [136], but also are only able to capture the "perceived" component of role ambiguity. Individuals may or may not be aware that they are working on things beyond their job requirements, such as when there is an information gap, or if they are investing their effort to gain knowledge and experience [47, 81]. Thus, it is unclear how useful these measures are [116], and researchers have argued that the lack of an instrument capable of measuring objective and perceived facets of ambiguity may have impeded both theory development and application of research results [16].

Further, with the development and adoption of technology in several sectors of the workplace, the landscape of work is evolving at an unprecedented speed. This also demands continuous skill development [24, 75]; a recent study by McKinsey Global Institute predicts enormous workforce transitions in the years ahead, estimating by 2030, as many as 375M workers globally will likely need to transition to new occupational categories and learn new skills [93]. However, there is no defined approach for organizations to proactively gauge individuals' fit with their assigned roles, no guidance for interventions to help them overcome role ambiguity. An organization that can proactively deal with role ambiguity will benefit from employees with increased satisfaction, wellbeing, and productivity in general.

Our study contributes to the above research gap and advances the theory by introducing a novel way of measuring role ambiguity. To the best of our knowledge, our study is the first to empirically and objectively measure role ambiguity via LinkedIn, a professional social networking platform where career profiles are publicly shared by employees with self-descriptions of their job titles and role descriptions. Juxtaposing traditional surveys with modern sensor derived measures of wellbeing, we combine methods adopted from natural language analysis and statistical modeling to examine the relationship of LinkedIn based role ambiguity (`LibRA`) with the wellbeing and job performance of individuals — the two important facets corresponding to one's job satisfaction [127].

Aim 1. To measure role ambiguity using unobtrusively obtained LinkedIn data.
Aim 2. To examine the relationship of Linkedin based Role Ambiguity (`LibRA`) with individual wellbeing and job performance.
Aim 3. To investigate what factors may contribute to one's `LibRA`, relating to their intrinsic traits, LinkedIn's platform-specific characteristics, and preferences and goals of use of professional social networking service.

For our first research aim, we model LinkedIn based Role Ambiguity (`LibRA`) as a lexico-semantic difference between the job description of an individual's role as self-portrayed on their Linkedin profile and what is posted by the company for that particular role. To compute this difference, we first employ natural language analysis techniques of word-embeddings to obtain the vector representations of job descriptions along eight facets of job role, namely *abilities, interests, knowledge, skills, work activities, work context, work styles, and work values* [141].

In our second research aim, in a theoretically grounded fashion, we test for hypotheses that examine the relationship of `LibRA` with an individual's 1) wellbeing related measures, namely their heart rate, arousal, sleep, and work-hours, and 2) job performance related measures, namely their individual task performance, in-role behavior, and organizational citizenship behavior. Our findings align with the propositions put forth by role theory, that greater `LibRA` measure is associated with factors that are related to depleted wellbeing such as, increased heart rate, increased arousal, decreased sleep, and decreased work hours, and is associated with lower job performance such as decreased task performance and decreased organizational citizenship behavior.

Finally, in our third research aim, we reflect back to investigate what factors contribute to `LibRA` as a measure. We contextualize one's self-presentation behavior on LinkedIn, by situating our observations in the literature on social sciences, social computing, and organizational studies. Our observations make valuable insights into the unobservable and unaccounted factors, such as an individual's mindset, job-related motivation, and platform-related nuances.

We discuss the theoretical, practical, and design implications that surround this new measure of role ambiguity assessed from people's professional social networking data, from the perspective of employees, organizations, and social computing platforms. Our research contributes to the growing interest on the topic of "Future of Work at the Human-Technology Frontier"[1], wherein we present new technology-facilitated means to improve workplace "health", performance, and functioning.

Privacy, Ethics, and Disclosure. This work is committed to secure the privacy of the employees and their employers, whose data on individual difference attributes are used. These individuals signed informed consent to provide the survey responses as a part of the Tesserae study, which was approved by the relevant Institutional Review Boards at researcher institutions. In addition, despite working with publicly posted job descriptions on websites such as LinkedIn, Glassdoor, Indeed, and company websites, this paper anonymizes each of these job titles and job descriptions. Finally, this paper reports paraphrased excerpts of LinkedIn self-described portfolios of the individuals. Together, these measures balance the sensitivity of privacy, traceability, and identifiability, as well as provide a context in readership. Even accounting for the benefits, we recognize and acknowledge the limitations of our methodological approach, and the potential misuses, risks, and ethical consequences involved with this kind of research, which we elaborate in Section 7.

2 BACKGROUND, THEORETICAL UNDERPINNINGS, AND RESEARCH AIMS

2.1 Role Ambiguity in Organizational Psychology

The theory of organizational role dynamics outlines role conflict, role ambiguity, and role overload as aspects of the job role that contribute to workplace stress [11, 112, 116]. Organizational psychology literature emphasized these characteristics of job role for at least five decades now and ample empirical evidence exists as to how role ambiguity impacts psychological wellbeing and productivity of individuals [79]. Kahn et al. defined role ambiguity as "*the discrepancy between the information available to the person and that which is required for adequate performance of his role*".

Over the years, surveys have been used to measure role constructs, and there has been no consensus on the quality of the measure [116, 134]. In surveys, *role conflict* is measured by asking individuals if they had to cater to addressing multiple co-worker needs simultaneously, and if they have to break rules to get things done. *Role ambiguity* is measured using responses to whether there

[1] *https://www.nsf.gov/eng/futureofwork.jsp*

are defined objectives for the role and if they can be well predicted by employees. *Role overload* is measured by the perception of employees, if they can get work done in available time and if a lot more is expected from them [112]. Among these, role ambiguity is prone to more significant changes and is more dynamic owing to the technological evolution in the industry. According to the role theory, role ambiguity is associated with the increase in the likelihood that the individual would be dissatisfied with their role, would experience anxiety, and would thus perform less effectively [117].

Since role ambiguity revolves around the expectations surrounding one's job role, this paper leverages an unobtrusive data source (self-described / self-presented) professional portfolio on social media (LinkedIn) to infer their role ambiguity. We validate our measure of role ambiguity on the basis of theoretically driven hypotheses, grounded in the literature on the relationship of role ambiguity with wellbeing and performance, which we discuss in the following two subsections.

2.1.1 Role Ambiguity and Wellbeing. Research has demonstrated that role ambiguity has negative consequences on employee wellbeing [134]. Role ambiguity is one of the antecedents of job satisfaction, and an increase in job satisfaction leads to lower stress [139] and higher intrinsic motivation of employees [158]. When employees are intrinsically motivated, they tend to have lesser somatic symptoms and lower anxiety [90]. In tune with the traditional principal-agent problem, lower intrinsic motivation leads to a lesser effort expended by employees at work [46].

While there is no single conceptualization of wellbeing, the broad categories that wellbeing encompasses are physiological, psychological and behavioral aspects [78, 127]. Physiological indicators include factors such as blood pressure, heart conditions, and general physical health. Psychological indicators include affect, frustration, anxiety, stress, and arousal. Behavioral aspects include those that an employee has a choice to make, like the time spent at work, the time taken for breaks during work, mobility to another employment (turnover), hours of sleep, etc.

Within the scope of our dataset, we study the relationship of `LibRA` with one's physiological measures (heart rate and sleep [21, 25]), psychological measures (stressful arousal [139]), and behavior at the workplace (time spent at desk and time spent at workplace [162]). Specifically, we test for the following hypotheses in the relationship of `LibRA` with wellbeing attributes.

H1. Greater role ambiguity is associated with increased heart rate.
H2. Greater role ambiguity is associated with increased arousal.
H3. Greater role ambiguity is associated with decreased sleep.
H4. Greater role ambiguity is associated with reduced work-hours.

2.1.2 Role Ambiguity and Job Performance. While job satisfaction is an important antecedent of job performance, the others include employee motivation and engagement. A more comprehensive explanation of job performance alludes to taking into account intrinsic motivation and employee engagement [77, 115, 125], which are shown to be determinants of effort exerted by employees. Such discretionary effort by employees improves their engagement with the organization [97]. Employee engagement has been defined in many ways [92], with satisfaction and motivation being core components. In fact, motivation has been perceived as employee engagement in a number of prior work [130, 156]. Yun et al. provide evidence that role ambiguity moderates the relationship between self-enhancement motive and job performance of an individual [160].

Role ambiguity consists of the uncertainty regarding tasks that an employee needs to perform as part of their job role in the company. An employee with greater clarity will be able to better perform the required tasks. One plausible mechanism that can explain this higher performance is the intrinsic motivation of an employee [90, 117]. Lower role ambiguity or higher role clarity makes it easier to meet the expectations, the employee more motivated and such intrinsically motivated employees perform better and more efficient [46, 48]. Employees with higher job satisfaction are intrinsically motivated and strive harder at work which contributes to their performance. Thereby, the exposure to role stressors (such as role ambiguity) affects an individual's capacity to control their work environment, which in turn adversely affects their ability to function effectively [88, 99].

Within the scope of our dataset, we study the relationship of `LibRA` with two dimensions of job performance [118, 154, 157] — 1) task performance and 2) organizational citizenship behavior. Here, *task performance* is a combination of individual task proficiency (three-item scale) [58] and in-role behavior (seven-item scale) [157]. Both of them measure the ability of an individual to adequately execute their assigned duties, and their proficiency at performing activities that drive an organization's *technical core*, or production processes that drive the conversion of input into output [143]. On the other hand, *organizational citizenship behavior(s)* is a set of pro-organizational actions that are not formally rewarded but demonstrate how an individual contributes to welfare and effectiveness within the organization [106, 111, 128]. Examples include helping other co-workers, kind gestures like volunteering in activities that are not part of work, or strictly adhering to rules at the expense of personal convenience. These are subjective and self-reported/assessed measures of job performance and we do not use any objective measures or supervisor/peer- assessments like ratings, evaluations, sales or profits, which are more likely to suffer from leniency, halo error, criterion contamination and deficiency [65, 70]. Prior literature in organizational behavior dominantly uses these subjective measures and we rely on the extant literature for the validity of these measures [154]. We test the following hypotheses for `LibRA` with respect to job performance.

H5. Greater role ambiguity is associated with decreased task performance.
H6. Greater role ambiguity is associated with decreased organizational citizenship.

2.2 Social Media Technologies and Workplace Behavior

In the last decade, researchers have used social media technologies to understand employee behavior at workplaces [33]. In their seminal work, Ehrlich and Shami compared employees' use of social media platforms inside and outside the workplace, particularly their motivations in their use of social media, particularly Twitter [40]. They report that social media use (both at home and work) made workers, especially mobile workers, feel more connected to other employees, and provided an avenue to boost personal reputation at the workplace. Studies also found that social media use is positively correlated workplace wellbeing [131]. Increased social media interactions within the workplace, through platforms such as IBM's Beehive, were found to improve both personal and professional networking, career advancements, and innovation [36, 37, 42, 50]. Other works find positive relationships between workplace and employee behavior, such as wellbeing, experiences, and engagement through social media technologies [33, 41, 44, 61]. In an early work, Skeels and Grudin conducted a longitudinal study of the motivations and use of social media platforms by workplace employees [135]. Taken together, social media use, both in and outside of the workplace contribute to the wellbeing and professional benefits through increased connectivity, reputation building, and networking opportunities.

In the same body of research, social media and online engagement platforms have facilitated an effective means to study employee behavior and satisfaction — a body of research that is extensive in CSCW and HCI area [5, 33, 105, 130, 132, 135]. A variety of analytical and computational approaches on language and network dynamics have been applied to glean correlates of employee job satisfaction and wellbeing, such as engagement [66, 105, 130], employee affect [33, 121], social pulse [131], reputation [74], organizational relationships [17, 52, 104], and workplace behavior [94]. Lee and Kang used Glassdoor data to study the influence job satisfaction factors, and their influence on employee retention and turnover [89]. These studies indicate the value of such unobtrusive data sources in understanding workplace experiences.

In the professional networking space, LinkedIn has emerged as the primary social media platform [140, 148]. This platform, which was initially viewed as a "repository of webpages", gradually evolved to be informally known as "Facebook in a suit" [5, 151]. LinkedIn allows the individuals to self-describe and self-promote their professional portfolio to either seek for new jobs, or to use it as their professional networking and webpage. Guillory and Hancock found that the public-facing nature of LinkedIn influences an individual's accountability and reduces deception in their self-description of their professional portfolio, which also aligns with Donath et al.'s early research on identity and deception in online spaces [38]. Researchers have studied the differences and similarities in the self-presentation behavior and use of LinkedIn in comparison to personal social media platforms such as Facebook and Twitter [5, 135, 151, 163]. In fact, organizations' use of LinkedIn has grown tremendously over the years, which also implicitly puts peer- and societal- pressure on individuals to own and maintain LinkedIn accounts [84]. Utz and Breuer recently studied the individual-specific factors that influence their behavior on LinkedIn in terms of networking and informational benefits that the platform facilitates [149], van de Ven et al. inferred personality traits on LinkedIn self-presentations of individuals, and Zide et al. studied how LinkedIn profiles differ across occupations. Zhang et al. studied employees' privacy perceptions on social media [163].

While all these sources are combined under a broad umbrella of 'social media', the motivations to use any of these platforms might differ based on individual and platform-specific characteristics [5, 33, 40, 120, 163]. On LinkedIn, the primary motivation to use is to gain professional visibility [5, 20, 85]. This professional visibility might be used by individuals to find jobs or switch jobs, or escalate to a better position within the same job, or to reach out to a broader community in general (like students in case the focal individual is in academia, or venture capitalists and funding agencies if the individual is in top management teams of start-ups) [5, 135]. Since preparing this profile is an exercise that makes the individual reflect upon their work, it also motivates to work towards building a better profile or developing new skills that would enhance their profile. While such motivation [49] leads individuals to work towards their personal goals, these goals might not align with organizational goals and this friction might contribute to stress leading to lower employee wellbeing, or can improve productivity because the employee works harder [161].

Our third research aim draws upon the literature in organizational studies, along with the literature to contextualize and discuss the unaccounted factors that may affect one's activity and self-presentation behavior on social media, and in turn, influence our measure of `LibRA`. Further, building on this body of work, our study leverages LinkedIn data to infer role ambiguity, a role-construct drawn on organizational psychology research, and then validates theoretically grounded hypotheses of individual wellbeing and performance. In doing so, we extend the CSCW community's long-drawn interest in understanding the role of technology in the workplace and on work (e.g., [110]) by investigating (social computing) platform, individual, and organization-specific complexities that should be considered to reliably and practically implement a measure like `LibRA`.

3 STUDY AND DATA

3.1 Study: The Tesserae Project

Our dataset comes from a large-scale multi-sensor study of workplace behaviors, called the Tesserae Project [98, 103]. This study, that was approved by the Institutional Review Board (IRB) at the researchers' institutions, recruited 757 participants[2] who are information workers in cognitively demanding fields (e.g. engineers, consultants, managers) across the United States. These participants who were recruited from January 2018 through July 2018, completed an initial set of questionnaires related to demographics, job performance, personal attributes, and wellbeing, administrated via psychometrically validated survey instruments, as well as received daily surveys on a set of these attributes. Participants also received three sensors: location-tracking Bluetooth beacons; 2) a wearable; 3) a phone agent—a smartphone application [155]. In addition, some participants authorized collection of their historical social media data. As compensation, participants either received a series of staggered stipends totaling up to $750 or they participated in a set of weekly

[2]Note that this is still an ongoing study and this paper uses the passively sensed data collected until November 13th, 2018. A random sample of 154 participants in our study was "blinded at source" to the researchers, and their data is put aside only for external validation at the end of the study period.

lottery drawings (multiples of $250 drawings) depending on their employer restrictions. Because the participants were enrolled over a 6 month period of time (January to July 2018) in a staggered fashion, data collection varied with a range of time between 59 days and 97 days (68 days on an average) (see Fig. 1(a) for the distribution).

Participant Privacy and Consent. Given the sensitive nature of the data being collected, participant privacy was a key concern in the study. The participants were provided with an informed-consent describing each sensing stream, and technical specifications listed what each device was capturing and how it would be secured and stored. The participants needed to consent to each sensing stream individually, and they had the provision to clarify their queries / concerns about the sensing streams, and they could opt out of any of them [98]. Their data was de-identified and stored in secured databases and servers which were physically located in one of the researcher institutions, and had limited access privileges. Participants were made aware that they could voluntarily drop out via an email at any point during the year-long study period. Participants could also specifically request their data deletion from the database.

3.2 Social Media (LinkedIn) Data

Participants authorized access to their social media data through an Open Authentication (OAuth) based data collection infrastructure that was developed in-house [119, 121]. In particular, we asked permission from participants to provide their Facebook and LinkedIn data, *unless they opted out, or did not have either of these accounts*. Note that we asked consent from only those participants who had existing Facebook or LinkedIn accounts from before the study. The participants could also optionally authorize their Twitter, Instagram, GMail, and Calendar data.

Out of the 757 participants in the study, 529 provided their LinkedIn data. Our work accounts for those with self-described portfolios and their passively sensed and self-reported wellbeing and job performance data. Therefore, we filter out "blinded" participants and those without any self-description in their LinkedIn profile, particularly in their profile and job summary, leading us to a LinkedIn dataset of 257 individuals — all the ensuing analyses in this paper is limited to these 257 individuals' data. Corresponding to every participant, we obtained their self-presented profile and job summary which includes current and previous jobs. Fig. 1(c) shows the top job titles in our dataset, and Fig. 1(d&e) shows two word-trees of profile summaries on two top representative keywords ("professional" and "skill") in our dataset. These word-trees give a sense of how individuals self-present their job summaries on their LinkedIn profiles; for example, within skills, we find occurrences of both tangible/technical skills (eg. *sap, technology, sales, microsoft office*) and intangible/people skills (eg. *leadership, communication, analytical, interpersonal*).

3.3 Self-Reported Data

As mentioned above, the enrollment process consisted of responding to a set of initial survey questionnaires related to demographics (age, sex, education, type of occupation, role in the company, and income). Participants were additionally required to answer an initial ground-truth battery, a set of survey questionnaires that measured their self-reported assessments of personality traits and executive function. Throughout their study period, they received daily or periodic validated surveys that recorded their self-reported assessments of job performance.

Fig. 1b plots the demographic distribution in this dataset. The 257 participants with *complete* LinkedIn data consist of 150 males and 107 females. The average age of the participants is 35.2 years (stdev. = 9.5). These participants belong to 60 unique companies, and among these, the top three companies, 103 belong to C_1 (a large-scale multinational firm), 54 belong to C_2 (a mid-size product-centric firm), and 17 belong to C_3 (a research organization). In terms of job role, the data contains 128 supervisors and 139 non-supervisors. In job sector, 202 participants belong to Non-IT sector, and 55 participants belong to the IT sector. In terms of tenure, while a majority of the individuals (53) have been at their current organization for over eight years, 113 individuals have

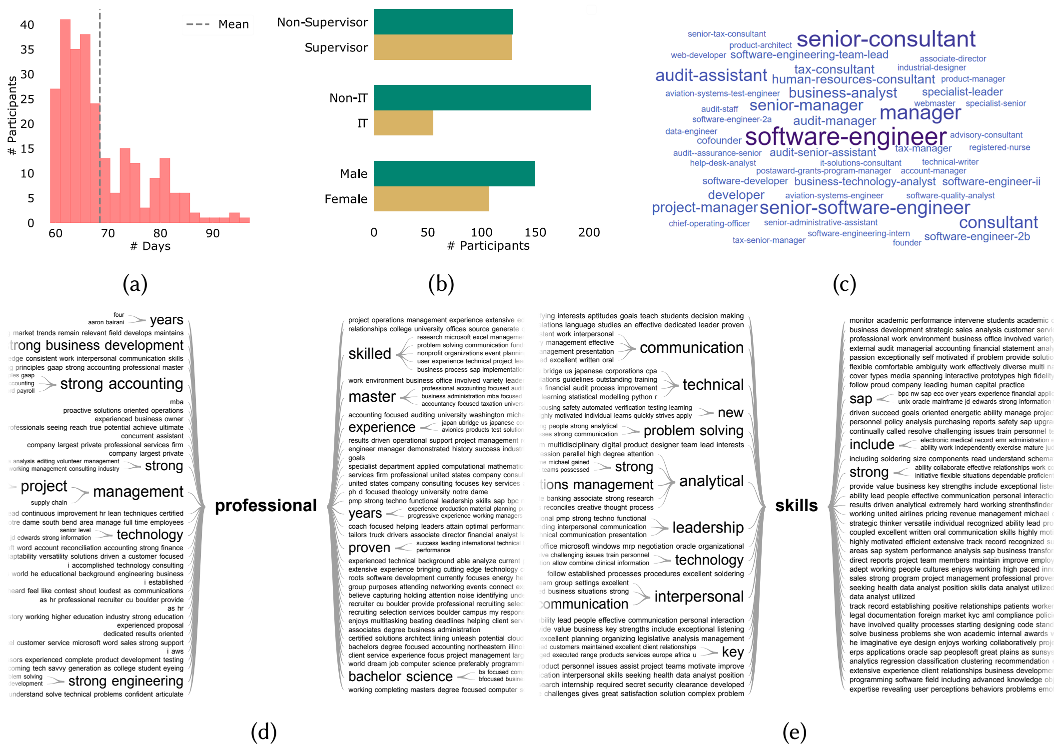


Fig. 1. Distribution in the dataset on (a) study period per participant, (b) demographic and job-role based characteristics, (c) word-cloud on the job roles on LinkedIn data, (d&e) Word tree visualizations on two top-occurring keywords (professional and skills) in the LinkedIn profile descriptions: These visualizations represent the content in the form of co-occurrences of keywords in the dataset. The font size of keywords are proportional to their occurrence along with surrounding co-occurring keywords. For example, management profesional, technology professional, professional keywords, analytical skills, technological skills, etc.

been at their current organization between three to eight years, and 101 individuals have been at their current organization for less than three years. For education, most participants have a college (52%) or master's degree (35%). In income, the participants are more evenly distributed, with the majority (64%) of the participants similarly distributed in the 50K-75K, 75K-100K, and more than 150K USD income brackets.

Next, we discuss their self-assessed individual difference attributes. We obtained the participants' big-five **personality traits**, as assessed by the Big Five Inventory (BFI-2) scale [138, 142], and **executive function**, especially their fluid and crystallized intelligence, as assessed by the Shipley scale [23, 129, 133]. For personality traits, our dataset shows a mean openness of 3.86 (std. = 0.54), mean conscientiousness of 3.87 (std. = 0.66), mean extraversion of 3.41 (std. = 0.67), mean agreeableness of 3.85 (std. = 0.55), and mean neuroticism of 2.51 (std. = 0.77). For executive function, our dataset shows a mean fluid intelligence of 33.38 (std. = 4.18), and mean crystallized intelligence of 16.91 (std. = 2.79).

For job performance, we obtain two kinds of measures:

Task Performance. To assess task performance, we use two scales, IRB (In-Role-Behavior) [157] and ITP (Individual Task Proficiency) [58]. The IRB scale contains seven items including questions such as *adequately performed assigned duties, failed to perform essential duties, performed expected* *tasks,* etc., each of which can be rated on a scale of 1 (strongly disagree) to 7 (strongly agree). On the other hand, the ITP scale contains three items, *carried out core parts of the job well, completed core tasks well using standard procedures, and ensured that the tasks were completed properly*, each of which can be rated on a scale of 1 (very little) to 5 (a great deal). Together, these instruments measure an individual's ability to adequately execute their assigned duties, and their proficiency at performing activities that drive an organization's technical core [14, 154].

Organizational Citizenship Behavior. We administer the OCB scale to measure organizational citizenship behavior [45]. Organizational citizenship behaviors characterize an individuals activities that are not typically or formally rewarded by the management, or voluntary activities outside one's core responsibilities, but which promote the welfare and effectiveness of the organization and its members [26, 111]. The survey instrument contains eight items, each of which asks the participant to self-reflect (yes/no), if they, *went out of their way to be a good employee, were respectful of other people's needs, displayed loyalty to my organization, praised or encouraged someone*, etc.

3.4 Passively Sensed Behavior and Wellbeing Data

To passively sense participants' behavior and wellbeing measures of participants, the study deployed three modalities of sensing technologies [12, 98] — 1) **bluetooth beacons** were provided to the participants (two static and two portable Gimbal beacons [4]) to essentially sense their presence at work and home locations, and consequently to help assess their commute and desk time as well, 2) A **wearable** (Garmin Vivosmart [3]) was provided to each participant to continually track their health measures, such as heart rate, arousal, and physical activity in the form of sleep, foot steps, and calories lost, and 3) A **smartphone application** was installed on the participants' smartphones to leverage their smartphone based mobile sensors to track their mobility and physical activity [155].

4 MEASURING ROLE AMBIGUITY FROM LINKEDIN (LibRA)

Why LinkedIn? LinkedIn is a professional social networking platform (launched in 2003) that allows individuals to create and publish their professional profiles and describe and their portfolios. Although LinkedIn is biased towards individuals' positive self-presentation and self-promotion, the non-anonymity and public-facing nature of the platform also influences individuals to be less deceptive and more accountable in their profiles [60]. In line with Goffman's theory of self-presentation, LinkedIn provides an ideal platform for individuals to present their "professional" selves to the online audience [54, 151]. Because LinkedIn is a non-anonymous platform, where individual identity (at least the name) is disclosed, it somewhat helps promote trust and accountability on the platform [38]. Therefore, it suits the choice of our dataset where we seek to obtain self-presented portfolios of employees on their roles and responsibilities at organizations.

4.1 LibRA: LinkedIn based Role Ambiguity

Defining LibRA. Drawing upon the theoretical definition of role ambiguity given in Section 2, we operationalize LinkedIn based Role Ambiguity (`LibRA`) as the *quantified differences in the self-explained roles and responsibilities of the individual against that posted by the company for the same role in the organization.* For this, we first obtain the self-explained job summary from an individual's LinkedIn profile. Then, for each role, we obtain the company described job description by manually conducting search engine queries of the specific role and the company. These job descriptions are typically posted on job posting websites, such as *Glassdoor, LinkedIn, Indeed*, and the *Google job search portal* — where the Google job search portal collates both exact and nearest matching job descriptions from multiple websites, including company's own website, LinkedIn, Glassdoor, Indeed, etc, and sorts them in relevance to the search query. For instance, Fig. 2) shows an example LinkedIn role description and company-published role description for the same role of Software Development Engineer at the same location of the company. Two coauthors independently obtained the nearest matching job description per role and per company — there were very few (<20) instances when

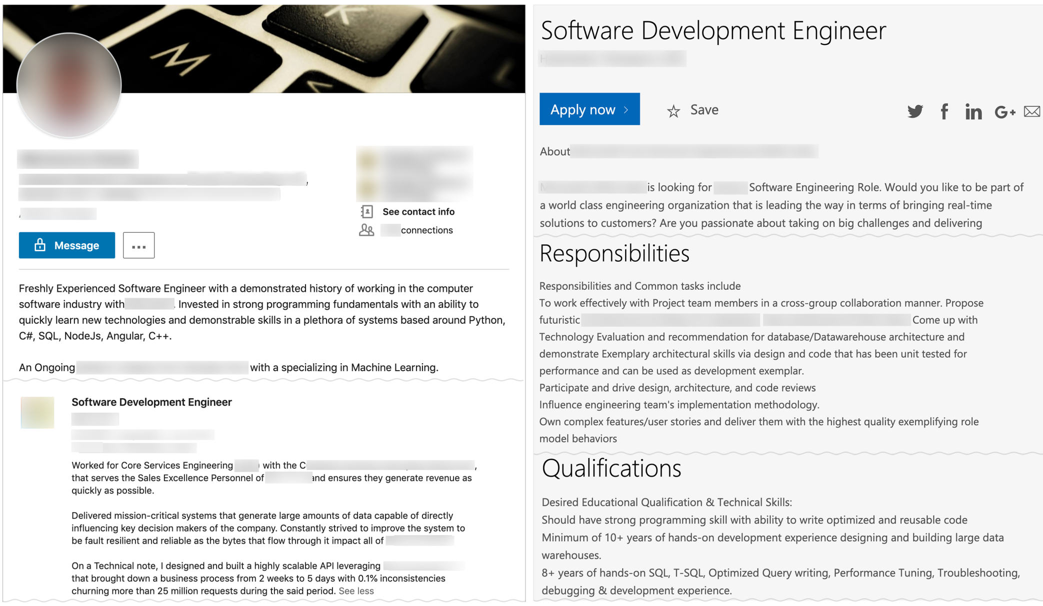


Fig. 2. For the same role (Software Development Engineer): (left) Role summary of an individual as described on LinkedIn, (right) Job description as posted on the company webpage

the two coauthors obtained different job descriptions, and when they did, the descriptions were very similar in the two websites, and the more relevant one was chosen.

Assessing LibRA. Next, towards computing LibRA, we first represent the above descriptions of self-reported LinkedIn job descriptions and the company described job descriptions in a multi-dimensional space of job aspects, for which we leverage O*NET. O*NET[3] is an online database and job ontology that contains a comprehensive list of jobs and their descriptions, elaborating on eight notable aspects of job role — *abilities, interests, knowledge, skills, work activities, work context, work styles, work values* (see Table 1 for brief descriptions). These aspects are grounded in literature and have been used in prior work to study employee behavior [141]. For every individual's role, we obtain their closest matching O*NET roles. For this, we adopt a semi-automatic approach of edit-distance based match, followed by manual evaluation and curation by two co-authors; the coauthors are familiar with, and are users of LinkedIn. For example, the closest match of *Software Development Engineer* is *Software Developers.*

Then, drawing on natural language analysis methods, we use word-embeddings, particularly pre-trained GloVe vectors [113, 123] to project the role descriptions of individuals and companies in a 50-dimensional word-vector space, so as to obtain rich lexico-semantic context surrounding the hand-curated job descriptors above [122]. We use cosine similarities to obtain two vector projections in the eight-dimensional job aspect space per individual i— 1) one that is obtained from their LinkedIn summary (v_1^i) and 2) one that is obtained from the same role's company description (v_2^i). Then, the overall LibRA is measured as the euclidean distance between v_1^i and v_2^i. To obtain the aspect-wise LibRA of an individual as the absolute difference per dimension of v_1^i and v_2^i. For instance, Fig. 3 show heatmaps of multi-dimensional role ambiguity of randomly selected 50 individuals

[3]O*Net (*onetonline.org*) is developed under the sponsorship of the U.S. Department of Labor/Employment and Training Administration (USDOL/ETA).

Table 1. Job aspect types with their descriptions as obtained from O*Net.

Job Aspect	Description
Abilities	Enduring attributes of the individual that influence performance.
Interests	Preferences for work environments and outcomes.
Knowledge	Organized sets of principles and facts applying in general domains.
Skills	Developed capacities that facilitate learning or the more rapid acquisition of knowledge.
Work Activities	General types of job behaviors occurring on multiples jobs.
Work Context	Physical and social factors that influence the nature of work.
Work Styles	Personal characteristics that can affect how well someone performs a job.
Work Values	Global aspects of work that are independent to a person's satisfaction.

Fig. 3. Aspect-wise LibRA for a random set of 50 participants in two companies C_1 (above) and C_2 (below). These visualizations are an example comparison of LibRA within- and across- company employees

from two companies, C_1 and C_2 in our dataset. We find that some individuals show high or low role ambiguity across the aspects, but most individuals show high role ambiguity in one or more dimensions. While exploring the differences across multi-dimensional role ambiguity constructs remain a future research goal, we envision that such multi-dimensional role ambiguity [134] can benefit various stakeholders (employers or employees) through guided intervention to minimize their role ambiguity. This kind of interface is additionally inspired from prior HCI work aimed at facilitating employee satisfaction [33, 131].

4.2 Evaluating the Validity of LibRA Against Gold Standard

After defining and proposing a method to measure LibRA using LinkedIn data of individuals, we examine the validity of the measure. That is, we examine if the LibRA measure gets at least close to what the Role theory identifies as "role ambiguity". For this, drawing on modern validity theory [29], we compare the LibRA of the individuals against a gold standard validated survey on measuring role ambiguity. The Michigan Assessment of Organization survey instrument measures an individual's role ambiguity, role conflict, and role overload [107]. Corresponding to role ambiguity, the scale asks the participants to rate the four statements, "Most of the times I know what I have to do on my job", "On my job I know exactly what is expected of me", "I can usually predict what others will expect of me on my job", and "Most of the time, people make it clear what others expect of me", a 7-point Likert scale ranging from "Strongly Agree" to "Strongly Disagree".

We randomly sample a subset of 77 participants from our entire participant pool to answer the Michigan Assessment of Organization survey [107]. Correlating the survey-based role ambiguity with LibRA, we find Spearman's[4] correlation coefficient to be 0.22 ($p < 0.05$).

[4]Because the survey instrument on role ambiguity and our measure of LibRA measure role ambiguity in different scale and order, it makes sense to correlate the ranked (or relative) values rather than the raw values

Table 2. Summary of covariates used in the regression models.

Covariates	Value Type	Values / Distribution
Demographic Characteristics		
Gender	Categorical	Male | Female
Age	Continuous	Range (22:63), Mean = 35.24, Std. = 9.46
Education Level	Ordinal	4 values [College, Grad., Master's, Doctoral]
Job-Related Characteristics		
Income	Ordinal	7 values [<$25K, $25-50K, ... , >150K]
Tenure	Ordinal	10 values [<1 Y, 1Y, 2Y, ... 8Y, >8Y]
Supervisory Role	Boolean	Supervisor | Non-Supervisor
Job Type	Boolean	IT | Non-IT
Executive Function (Shipley scale)		
Fluid (Abstraction)	Continuous	Range (5:23), Mean = 16.91, Std. = 2.78
Crystallized (Vocabulary)	Continuous	Range (0.0:40.0), Mean = 33.38, Std. = 4.18
Personality Trait (BFI scale)		
Openness	Continuous	Range (1.7:5.0), Mean = 3.86, Std. = 0.54
Conscientiousness	Continuous	Range (1.7:5.0), Mean = 3.87, Std. = 0.66
Extraversion	Continuous	Range (1.7:5.0), Mean = 3.41, Std. = 0.67
Agreeableness	Continuous	Range (2.1:5.0), Mean = 3.85, Std. = 0.56
Neuroticism	Continuous	Range (1.1:4.7), Mean = 2.51, Std. = 0.77

Consequently, a statistically significant correlation does imply criterion validity, and hints at construct validity in our claim that LibRA does contain information that is also captured by gold standard, validated survey instruments on role ambiguity. However, we also acknowledge that the magnitude of correlation is moderate, which could be attributed to the differences in the measures (one is "perceived", and other is objectively measured) — we revisit some of the other nuances and factors that may cause these differences again later (Section 6 and 7) in this paper.

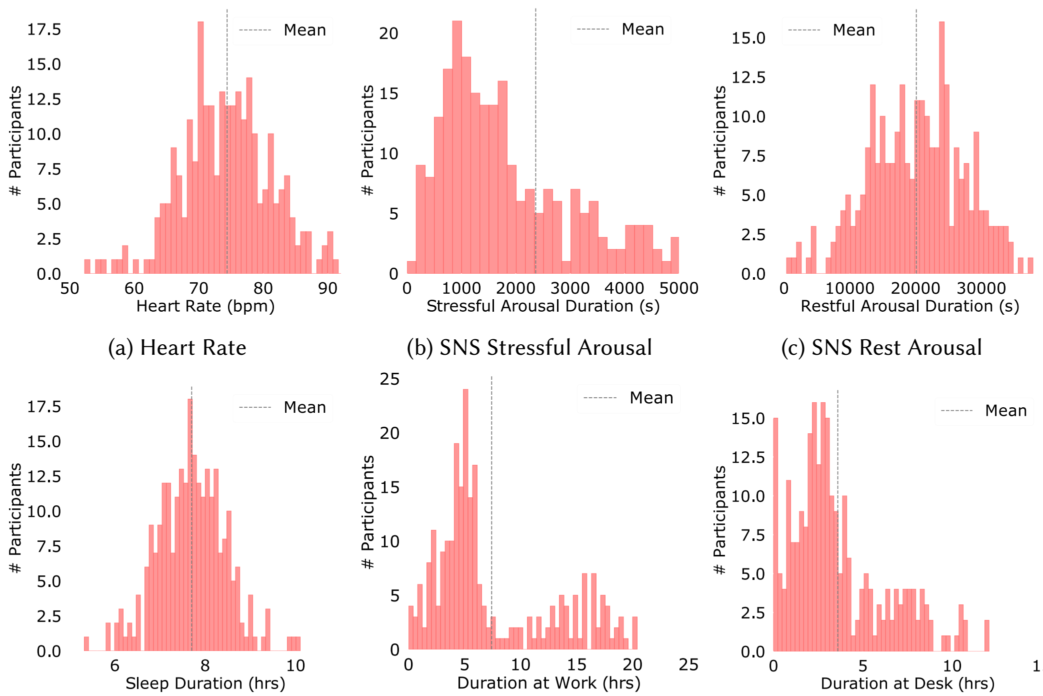
5 EXAMINING RELATIONSHIP OF LibRA WITH WELLBEING AND PERFORMANCE

This section revisits the hypotheses as outlined in section 2 towards establishing convergent validity of LibRA. For this, we study the relationship (and association) of LibRA with the passively sensed wellbeing measures, and the validated survey-based job proficiency measures. Because we are interested in studying the relationship, we consider linear regression models, which are known to provide easily interpretable associations in cases of conditionally monotone relationships with the outcome variable [32]. For every wellbeing or performance measure $\mathcal{M}$, we build linear regression models with $\mathcal{M}$ as the dependent variable, and LibRA as an independent variable, controlled for demographic, personality, and executive function measures per individual (see Equation 1). Our choice and inclusion of these covariates are motivated from prior literature [7, 15, 159]. Table 2 summarizes these covariates in their kind, and the values attained. For all the regression models, we use variance inflation factor (VIF) to eliminate multicollinearity of covariates (if any) [109]. For the ease of comparing the relative importance of the predictive variables in the regression models, we standardize their such that the variables have a mean of zero and standard deviation of one.

$$\mathcal{M} \sim gender + age + education\_level + income + supervisory\_role + tenure + job\_type \\ + executive\_function + personality\_trait + LibRA \tag{1}$$

5.1 LibRA and Wellbeing

5.1.1 H_1: Greater role ambiguity is associated with greater heart rate. High heart rate is associated with an increase in stress [9, 64]. Caplan and Jones found that greater role ambiguity is associated with increased heart rate, which is identified as a major predictor of coronary heart rate [9, 21].



(a) Heart Rate (b) SNS Stressful Arousal (c) SNS Rest Arousal

(d) Sleep (e) Duration at Work (f) Duration at Desk

Fig. 4. Distribution of wellbeing measures as inferred via passive sensors.

We obtain the heart rate measures of the participants through the wearable sensor (see Section 3, Fig. 4 (a)). We fit a linear regression model with the average heart rate (HR) in the study period per individual. Given that exercise and physical activity has an association with heart rate [55], in addition to the covariates listed in Table 2, we control for the physical activity per participant. The regression model reveals a positive standardized coefficient (0.10) with statistical significance for `LibRA` (Table 3, Fig. 5 (a)). This observation supports our Hypothesis H_1.

5.1.2 H_2: Greater role ambiguity is associated with greater stressful arousal. Arousal is a physiological response that is related to one's heart rate variability, and is associated with stress, fatigue, and anxiety [35, 64]. These wellbeing measures are known to exacerbate in the presence of role ambiguity [1, 21]. In our project, the wearable sensor allows us to obtain participant arousal, particularly their Sympathetic Nervous System (SNS) arousal measures in a continuous fashion. In particular, for every individual, it scores the arousal level from restful to stressful on a scale of 1-100 at every three-minute granularity (Fig. 4 (b&c)). Here, the restful duration is when an individual relaxes or recovers from stress [3]. We build two separate regression models, one with median duration of high stressful arousal (75-100), and one with median duration of restful arousal (1-25) per individual. We find that `LibRA` shows a positive standardized coefficient (0.42) in the former model, and a negative standardized coefficient (-0.22) in the latter model (Table 3, Fig. 5 (b&c)). This suggests that individuals with high `LibRA` are more likely to show higher stressful arousal, and lower restful arousal. Therefore, our observations support H_2.

5.1.3 H_3: Greater role ambiguity is associated with decreased sleep. Sleep is an important attribute in an individual's wellbeing, and it reduces the negative impact of stress as well as improving

Table 3. Summary of standardized coefficients of regression models of wellbeing.

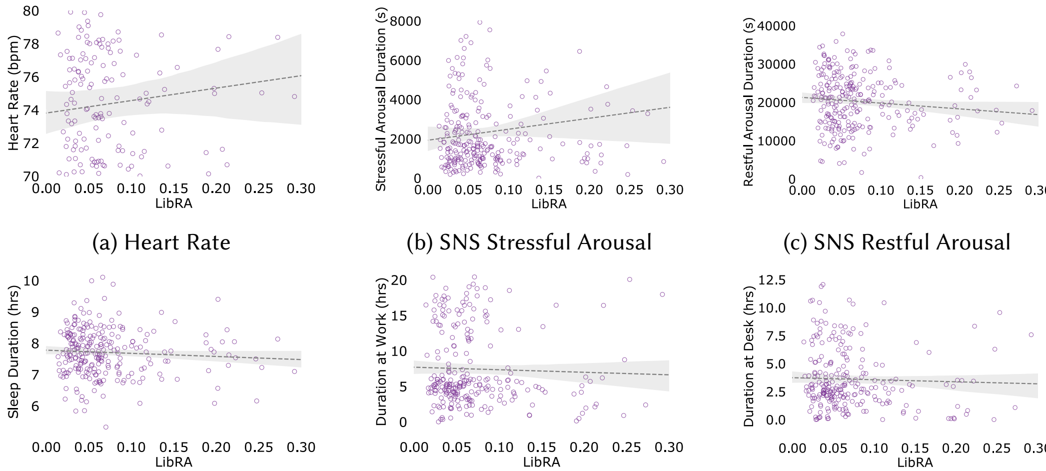
Covariates	Std. Coeff.	Covariates	Std. Coeff.	Covariates	Std. Coeff.
H_1 (Heart Rate)		H_2 (Arousal)			
$\mathcal{M}$ = Heart Rate, $R^2 = 0.16^{*}$		$\mathcal{M}$ = Stressful Duration, $R^2 = 0.65^{*}$		$\mathcal{M}$ = Restful Duration, $R^2 = 0.47^{**}$	
Exercise Duration	0.53**	Age	0.69**	Job: Non-IT	0.31*
Shipley: Abs.	-0.81*	Edu: Grad. School	-0.24*	**LibRA**	-0.22***
Agreeableness	0.91*	Tenure: 4	-1.59*		
Conscientiousness	-0.78*	**LibRA**	0.42***		
LibRA	0.10*				
H_3 (Sleep)		H_4 (Work-Hours)			
$\mathcal{M}$ = Sleep Duration, $R^2 = 0.19^{***}$		$\mathcal{M}$ = Duration at Work		$\mathcal{M}$ = Duration at Desk	
Income: $50K-75K	0.21*	Edu.: College	0.23***	Duration at Work	0.18*
Agreeableness	-0.14*	Edu.: Grad. School	0.21***	Edu: College	-0.09
Tenure: 7 Yrs.	-1.74*	Income: $50K-75K	0.14***	Edu: Grad.	-0.04
Job: Non-IT	0.15**	Income: $100K-125K	-0.18***	Edu: Master's	0.04
LibRA	-0.16***	Shipley: Abs.	0.01***	Income: $100K-125K	0.09*
		Extraversion	0.09***	Income: $125K-150K	0.08*
		Conscientiousness	0.05***	Tenure: <1 Yr.	-0.18***
		Neuroticism	0.12**	Tenure: 2 Yrs.	0.18***
		Tenure: 6 Yrs.	-0.16***	Tenure: 3 Yrs.	0.26***
		Tenure: 7 Yrs.	-0.15***	Tenure: 4 Yrs.	0.09***
		Tenure: 8 Yrs.	-0.31***	Tenure: 8 Yrs.	0.15***
		Job: Non-IT	0.20***	Job: Non-IT	-0.03*
		LibRA	-0.41***	**LibRA**	-0.12**

overall health [13]. Given that stress reduces sleep, and sleep reduces stress, a stressed person is likely to sleep less [152]. If role ambiguity is stressful, we hypothesize that high role ambiguity will correspond with reduced sleep duration. The wearable sensor allows us to obtain participant sleep durations (see Fig. 4 (d)). We build a linear regression model with median duration of sleep per individual. We find that `LibRA` shows a negative standardized coefficient (-0.16) with statistical significance (Table 3, Fig. 5 (d)). Therefore, H_3 is supported in our dataset.

5.1.4 H_4: Greater role ambiguity is associated with decreased work hours. Role ambiguity is known to affect an individual's workplace behavior [112]. The bluetooth beacons sense if a participant is at work, at home, or commute, and within work; it additionally captures the duration the participant is at- and away from- desk. We build two regression models, one with the duration at work, and one with the duration at desk, when at work (this model additionally controlled for duration at work). Here, we find that both of these dependent variables show heavy-tailed distributions (see Fig. 4 (e&f). For both of these distributions, Chi-squared tests could not reject the null hypotheses that they were significantly different from a Poisson distribution ($p > 0.05$). Therefore, instead of using purely linear regression models, we build negative binomial regression models [67], ones that essentially regress the logarithm of the dependent variables with the independent variables [67]. We prefer negative binomial regression over poisson regression because we find the presence of over-dispersion in the distribution of both duration at work and duration at desk (Fig. 4 (e&f)) [30]). We find that `LibRA` shows a negative standardized coefficient in both the models (-0.41 for duration at work, and -0.12 for duration at desk, Table 3, Fig. 5 (e&f)). This suggests that individuals with high `LibRA` are not only less likely to spend time at work, but also less likely to spend time at desk when at work. These observations support H_4.

5.2 LibRA and Job Performance

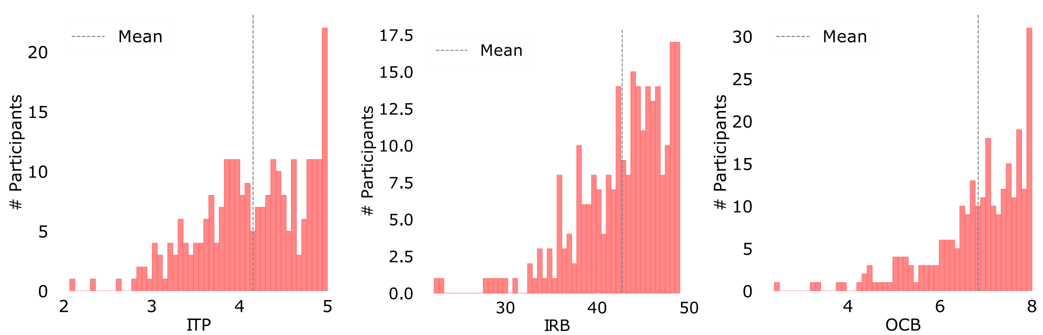
5.2.1 H_5: Greater role ambiguity is associated with lower task performance. We administered two survey scales of In-Role Behavior (IRB) and Individual Task Performance (ITP) three times a week,



(a) Heart Rate (b) SNS Stressful Arousal (c) SNS Restful Arousal

(d) Sleep (e) Duration at Work (f) Duration at Desk

Fig. 5. Scatter plots of demonstrating the distribution of wellbeing attributes against LibRA. LibRA is positively associated with heart rate, stressful arousal, and negatively associated with restful arousal, sleep, duration at work, and duration at desk. In sum, increase in LibRA is associated with depleted wellbeing.



(a) ITP (b) IRB (c) OCB

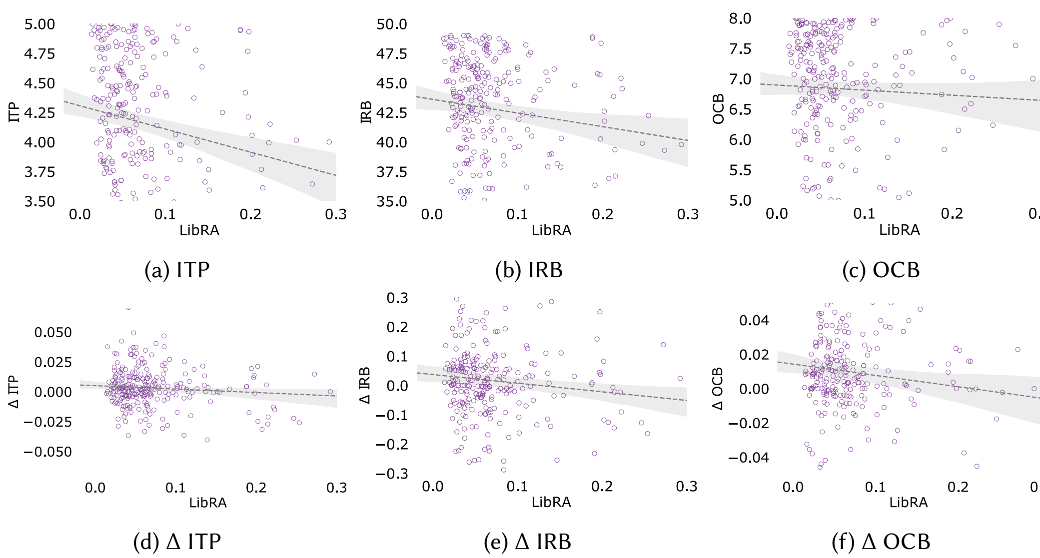
Fig. 6. Distribution of Performance measures via job performance surveys.

to periodically obtain the self-assessed task performance of the participants (see Section 3, Fig. 6 (a&b)). For both these measures, we build two linear regression models each — one that uses an aggregated (median) value of task performance, and one that uses a change in task performance over the duration of the study. We find that LibRA shows a negative association with both *aggregated ITP* (-0.33) and *change in ITP* (-0.20) per individual. Similarly, LibRA also shows a negative association with both *aggregated IRB* (-0.29) and *change in IRB* (-0.20) per individual (Table 4, Fig.7 (a&b, d&e)). Together, these observations suggest that individuals with higher LibRA not only have a greater likelihood of performing badly at work, but also their performance worsens over time. Therefore, our observations support H_5.

5.2.2 H_6: Greater role ambiguity is associated with lower organizational citizenship behavior. We administered the Organizational Citizenship Behavior (OCB) scale three times a week, to periodically obtain the self-assessed organizational citizenship behavior of the participants (Fig. 6 (c)). Like the

Table 4. Summary of standardized coefficients of regression models of task performance.

Covariates	Std. Coeff.	Covariates	Std. Coeff.	Covariates	Std. Coeff.
H_5 (Task Performance)				H_6 (Org. Citizenship Behavior)	
$\mathcal{M}$ = ITP, R^2 = 0.29***		$\mathcal{M}$ = IRB, R^2 = 0.29***		$\mathcal{M}$ = OCB, R^2 = 0.24***	
Income: L	-0.38*	Openness	0.13**	Supervisor: Yes	0.24***
Income: Q	0.40**	Consc.	1.13*	Extraversion	0.34***
Openness	1.07*	Tenure: 8	0.17*	Tenure: 6	-0.14*
Consc.	1.30***	**LibRA**	-0.29*	Tenure: 7	-0.20**
Tenure: 6	-0.15*			**LibRA**	-0.10**
LibRA	-0.33***				
$\mathcal{M}$ = Δ ITP, R^2 = 0.13*		$\mathcal{M}$ = Δ IRB, R^2 = 0.17***		$\mathcal{M}$ = Δ OCB, R^2 = 0.22*	
Extraversion	0.69*	Openness	0.91**	Supervisor: Yes	-0.26*
Consc.	-1.37***	Consc.	-0.84*	Agreeableness	-1.80*
LibRA	-0.20*	Tenure: 7	-0.19*	Tenure: 5	0.21*
		Tenure: 8	-0.26**	**LibRA**	-0.25***
		Tenure: 9	-0.18**		
		LibRA	-0.20**		



(a) ITP (b) IRB (c) OCB

(d) Δ ITP (e) Δ IRB (f) Δ OCB

Fig. 7. Scatter plots of demonstrating the distribution of job performance measures against LibRA. LibRA is negatively associated with ITP, IRB, OCB, Δ ITP, Δ IRB, and Δ OCB. In sum, an increase in LibRA is associated with both decreased job performance as well as reduced job performance over time.

above, we build two linear regression models — one that uses an aggregated (median) value of OCB, and one that uses a change in OCB over the duration of the study. We find that LibRA shows a negative association with both aggregated OCB and change in OCB per individual (Table 4, Fig.7 (c&f)). These observations suggest that individuals with higher LibRA show a greater likelihood of poorer OCB, which also worsens over time — a tendency associated with being disinclined to be altruistic or help colleagues at workplace. Therefore, our observations support H_6.

6 INVESTIGATING THE FACTORS AFFECTING LibRA

This final section studies the factors that contribute to the LinkedIn based role ambiguity (LibRA) assessment. Specifically, we investigate the extent to which appropriating data shared online (on a professional social networking service, LinkedIn) may bring forth new dimensions to consider while employing LibRA for practical use, and what might contribute to observed differences in LibRA. To do this, we draw from various literature to situate our observations.

First, we seek to quantitatively study the relationship of LibRA with observable and intrinsic attributes of an individual. Using the same covariates as in Table 2, we fit one's LibRA as the dependent variable in a series of statistical models. Our rationale to study this rests on prior work that found demographic and intrinsic traits affecting self-disclosure behavior on LinkedIn, which may lead to differences in LibRA [63, 144, 146, 150]. We build multiple regression models (both linear and non-linear), but find no significance in the relationship ($p > 0.1$) in either the regression fit or the variable coefficients. ANOVA F-test per covariate and LibRA reinforced our confidence in this finding that there is no significant relationship in the variability of observable traits influencing LibRA. This aligns with previous literature that claims role ambiguity is independent of individual traits, rather than an outcome of a number of factors such as mentor-mentee relationship, working alliance, organizational structure, and organizational communication [87]. Nevertheless, because LibRA is inferred from social media data, specifically LinkedIn, we recognize that numerous mediators can confound the self-presentation behavior of an individual on LinkedIn (even after controlling for their intrinsic demographic and personality traits). We delve deeper into this consideration based on a qualitative examination of a sample of our dataset as described below.

We intend to compare and study the self-presentation behavior, accounting for the between-individual differences in self-reported and assessed traits of demographic, personality, executive function, and work role-related characteristics. Therefore, with these characteristics as covariates (see Table 2), we draw on matching techniques from causal inference [71, 124] to match individuals using Mahalanobis Distance Matching [59]. We separately match pairs of individuals who belong to IT roles, and who belong to non-IT roles. Fig. 8 plots the pair-wise Mahalanobis distances and the absolute differences in their role ambiguities. We focus on those individuals (shaded region in Fig. 8) who are similar in their individual attributes but show high differences in their LibRA – we sample the top 10th percentile of pairs of individuals in IT and non-IT each.

Next, among the individuals in the above sample, we manually look at their (public) LinkedIn job and profile descriptions. While these individuals are very similar in their personality, demographic traits, and their role in the company (because of matching), in terms of their self-presentation behavior on LinkedIn, we find differences in their style of writing (also highlighted in the Fig. 8 examples). For example, one writes an extremely short description compared to their matched other, who writes a longer description with much more detail. Another example includes only technical-skills or the tasks that they are assigned at work (e.g., *Java, business development*), compared to their matched other, who additionally describes their non-technical and people skills and abilities (e.g., *accomplished, dynamic*). Given the affordances and the uniqueness of LinkedIn as a professional social networking platform, we deduce a few plausible reasons that can potentially influence the virtual self-presentation of the individuals, and in turn, lead to varied inferred role ambiguity. We discuss these factors, which are not disjointed and could be inter-related:

Individuals' Organizational Behavior. Individuals who are looking for newer jobs or endeavors possibly write a more detailed portfolio on their LinkedIn profiles, whereas individuals who are generally "settled" are not as active in providing detailed descriptions [135]. This could also be a *different type* of job than what they are currently involved at altogether as well. In other words, the settled people may have different jobs currently compared to they were hired, e.g., through promotion or lateral moves within the company. An alternative conjecture could also be that, only a few individuals write and "highlight" their *work experience*, rather than describing their responsibilities and tasks at the workplace, for example, "I have 25 years of Health Care Provider experience in revenue cycle selling and managing outsourced health care accounts, receivable solutions [..]". We find individuals who describe their role with people skills and proficiencies beyond their tasks, such as "I can effectively cope with change, shift gears comfortably, and bring

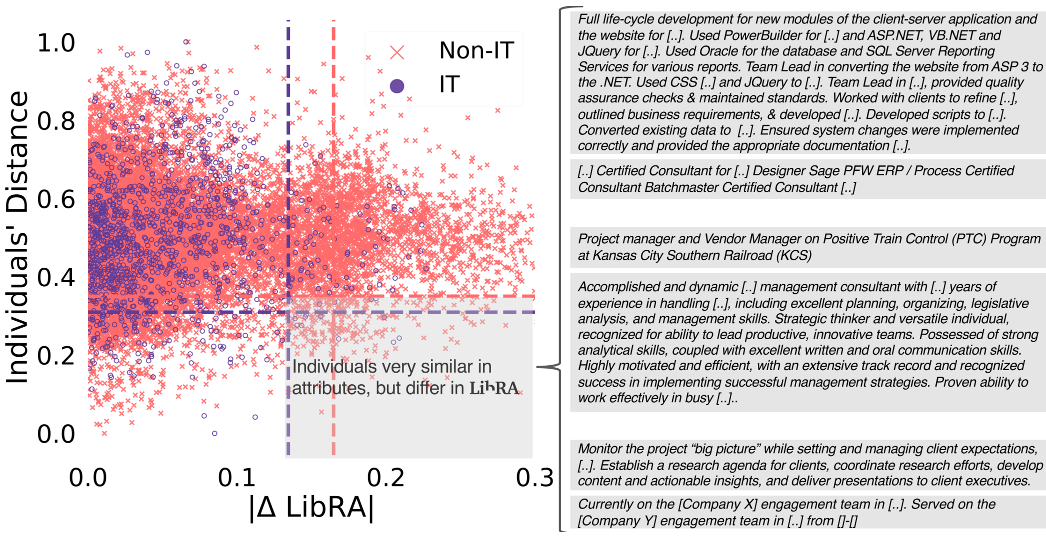


Fig. 8. Pair-wise differences in individual attributes and corresponding differences in LibRA. Example excerpts show the differences in LinkedIn descriptions of pairs of individuals with very similar individual attributes (low differences), but large differences in LibRA.

a point of view to the leadership", and those who describe their attitude towards initiativeness, "I am always willing to help especially if there is a problem to be solved, and my behavior is a mix of light-heartedness and a drive to put into practice everything I have learned.". These could be individuals who exhibit proactive behaviors in the organizations [27]: they show anticipatory, change-oriented and self-initiated behavior in situations and tend to act in advance of a future situation, rather than just react later. This may also indicate that although these individuals have high role ambiguity, they show desirable individual characteristics (proactive behavior and leadership traits) in organizations [8, 27]. Exploring these aspects further is of future research interest.

Individual-Intrinsic Factors. Prior research has observed that many individuals tend to self-promote and appear honest and less deceptive on their professional social networking profiles [60, 151]. However, the degree and the way in which they self-present themselves can vary. Given the context of professional choices and career development, we can look at it from the perspective of growth versus fixed mindset [39]. Those with "fixed mindset" believe their abilities are innate, whereas the ones with "growth mindset" believe that abilities can be acquired via investing effort and study. For instance, an individual describes themself as, "a motivated and hardworking professional looking to improve my skills and abilities." Although mindset and personality traits are somewhat related, mindset can reshape over time and through interactions [2]. Complementary research directions have also coined "benefit mindset", and "global mindset", "productive mindset", and "defensive mindset", all illustrating a variety of intrinsic behaviors of individuals that contribute to their skill development, proficiency, and self-presentation in organizations [18, 62]. We conjecture that similar traits permeate into their online self-promotion practices on LinkedIn.

Job-Related Factors. Literature has demonstrated the importance of job titles in organizations [147]. LibRA assessments of an individual are derived from the job titles of the individuals. However, if the job titles themselves are ambiguous then that inherently adds ambiguity to the role of the individual. In fact, we find pairs of individuals where one is an "Associate", while the other is a "Specialist" — both of these titles are pretty generic, and do not convey much information to the employees. In contrast, the fact that recently companies are coming up with "cool" job titles (e.g., *ninja*) to gain visibility and distinctiveness can add other complexities to role ambiguity [126]. As Utz and Breuer recently noted that one's career orientation, type of role or organizational sector, influence their behavior or use of LinkedIn— for example some sectors may require more referrals or information than others, thereby implicitly demanding greater activity from the individuals [149, 164]. Additionally, some individuals may be working on confidential projects and they are bound by nondisclosure agreements. Further, the role in a company and size of a company can influence the self-description behavior of individuals [164]. That is, even with common and similar job titles, individuals at large enterprises may not feel the need to describe their role in as much as detail as those at startups and mid-size organizations [95]. Compounding this difference in company size, some companies may encourage the use of LinkedIn among employees to improve the image of the company, or may even render the platform as a mandatory in-company communication tool, thereby influencing the LinkedIn use behavior of their employees [151].

Audience, Privacy, and Platform Factors. Finally, the familiarity or the use of LinkedIn as a platform may vary across individuals. Two participants in our sample described what their company does, rather than what their role is, such as, "[Company] specializes in [..] and works with companies that offer [..] service. [Company] has over 40 years of experience in the industry and operates groups of 10 to 1000 people [..]." In addition, LinkedIn is a professional social networking platform that also functions as a marketplace for job seekers. Individuals tend to share credible information because they have a conceptualization of an "invisible audience" [10], and since LinkedIn is a public space, they do not want to appear as dishonest [60]. At the same time, as discussed in Ghoshray's work, employee surveillance and employee's subjective expectation of privacy shares a competing relationship, and the sheer perception of being "surveilled" can influence one's self-disclosure behavior on the platform [51, 73, 146]. Further, employee's own mental models about LinkedIn privacy might be a factor behind what they share [22].

In summary, `LibRA` is based on self-presentation on a professional social media site, Linkedin. As such, it is subject to variability in self-presentation and motivation found in the population, such as differences in organizational behavior, differences in job status (e.g. looking for a new job vs remaining established), differences in values (e.g. "fixed" vs "growth" mindset), differences in the context of the job (e.g. a software engineer at a small firm vs a large firm) and the assigned job title, and differences in how individuals perceive the positives and drawbacks of their professional information in a publicly accessible space. These differences should be considered when applying `LibRA` in assessing role ambiguity. We discuss the consequences and implications associated with such a measure in the next section.

7 DISCUSSION

7.1 Theoretical Implications

This work measures role ambiguity (`LibRA`) for information workers with a diverse set of individual difference attributes using their self-described portfolios as shared on professional social networking website (LinkedIn). Traditionally, registries and census organizations have served as analogous source of data for people's professional portfolios. Our work reveals the feasibility of measuring a role related construct (here `LibRA`) at scale via a previously unexplored, low-cost, and unobtrusive source of data. Management and economics research is advancing in ways that can use this data to operationalize and derive existing measures (e.g., role constructs and role stressors) in novel ways. Thereby, our work revisits old questions in labor economics. While existing efforts so far have been limited to utilizing statistical numbers such as salary distribution, unemployment rates, and so on. Our work can potentially complement these with richer information on employee job satisfaction at scale.

This work lays the foundation of studying employee organizational psychology and behavior through unobtrusive online data sources, that set up marketplaces for employees, such as other professional networking websites such as Meetup, Xing, Jobcase, etc. Because our method is platform-agnostic, and such career portfolio like in LinkedIn is universally available, our work can be easy to replicate in other contexts such as diverse workplaces and organizations, and other types of situated communities. In addition, our work combines organizational psychology, organizational behavior, and organizational strategy streams of literature, and can further be used to advance our understanding of coping mechanisms, incentives, and job satisfaction in general at workplaces, by adopting a technology-focused and technology-driven lens.

Because this work uses individuals' self-described portfolios of job roles and responsibilities, we can to objectively assess the differences in "what the individual considers and self-describes themselves to be doing", and "what the company hired them for, or what their job description states". That is, the individual may only be showing normative and socially influenced behavior at their work, or show there is information gap, or demonstrate they intend to invest more effort to learn and gather experience themselves. These are behaviors that are detectable oblivious to the presence of role ambiguity. Such "unaware role ambiguities", is challenging to capture via survey instruments as they are tuned to measure the "perceived role ambiguity". Language can reflect differences in personal traits as well as situational ones [53]. This additionally makes our measure less subjectively biased than traditional methods of measuring role ambiguity.

7.2 Practical and Technological Implications

7.2.1 Individual-Centric Implications. From a practical implication perspective for an *individual*, our work can be used to develop self-reflection tools for employees to mitigate their intrinsic bias in perceived role ambiguity. This can help them continually assess themselves on their skillset and productivity at work. Such self-reflection tools can include within and across organizational role comparisons, and also within and across industrial role comparisons. These can potentially benefit the employees to have more streamlined information on their end that reduces their job search costs and effort, and enhances their wellbeing. In addition, describing tasks or job role in itself is partially a self-reflection process, and a tool that scores for a type of description will help minimize bias, and also help the employees to identify sources of their role ambiguity.

Further, self-reflection is known to have a positive influence on productivity and job satisfaction [34]. Integrating self-reflection tools with our approach would facilitate automated (self)-assessment of one's skillset, interest, and adaptability to an organizational role, and indirectly help them estimate their productivity, wellbeing, and job satisfaction at both their current as well as a future potential workplace. By logging roles, responsibilities, and tasks in a longitudinal fashion, an individual can assess their professional growth and development, and can also be prompted with recommendations for skill training wherever necessary. For the individuals who want to seek professional career-related advice, these logs can function as a diary-style data source to professional mentors and career counselors for better understanding of one's career trajectory, beyond the information presented in a resume.

7.2.2 Organization-Centric Implications. Presently job and skillset training at organizations is not streamlined [108]. Either they train a lot of employees in a batch, or they mentor them individually. However, with more information regarding how employees perceive their role, employers can identify the area of training required that will reduce role ambiguity and enhance the productivity of employees. With our method, since the time to identify such role ambiguity gaps can be reduced, both training costs and employee wellbeing costs for the organizations can be reduced. This in turn, can improve employee retention for companies by identifying turnover intentions.

Aligning with and confirming the literature [87], our findings suggest that LinkedIn inferred role ambiguity (`LibRA`) is not dependent on individual differences such as personality, gender, supervisory role, and executive function. This can inform organizations how these roles or titles can be transformed to match skill-level, task-assignment level, and incentive-level restructuring. In addition, this work calls for more careful development of job descriptions. Organizations can involve team- or sector- level staff in curating of job descriptions that are more attuned to the responsibilities and skills of the employees, and can dynamically update the descriptions in accordance with the necessity [69, 83]. Together, these measures can help improve job attractiveness and employee satisfaction in the company.

The interest in human resource management is still nascent but promising in the HCI and design community. In fact, cross-disciplinary literature pertaining to workplaces and online technologies provide potential use-cases urging the attention of designers [132]. Our work has implications towards designing and developing organization-centric technologies:

(1) First, tools can be built that suggest carefully chosen, fine-tuned job titles to companies, based on our measure of `LibRA` [6, 56]. This is particularly important because younger organizations sometimes offer (higher ranking or impressive-sounding) titles to employees in lieu of higher salaries, but this strategy has been reported to backfire due to increased role ambiguity and in turn, affecting employee productivity and wellbeing [126]. Adoption of tools that inform organizations about existing ambiguities in specific job roles, therefore, has the potential to make the workplace and individual roles more conducive to effective coping against workplace stress [88]. Moreover, professional social networking platforms (such as LinkedIn) are already heavily used to recruit by job agencies and resume matching consultancies [84]. Such agencies can leverage the insights gained from our approach to both match as well as recommend suitable jobs to prospective employees that are likely to result in lower role ambiguity.

(2) Second, our work can help design workplace tools and dashboards to enhance organization "health" or functioning. Such dashboards can unobtrusively and proactively assess employee role ambiguities at scale, taking employees' privacy considerations into account. In fact, many companies already provide their employees with internal social media platforms [36], online engagement forums, or even email profile description spaces, where they can regularly update their self-explained expertise and role descriptions, along with manager or peer-appraised testimonials. By leveraging such internal datasets, management in companies can potentially adopt these dashboards to gauge role ambiguity to make informed role matching for teams that require internal hires for open positions or internal role/team swappings. Companies can also restructure and reassign current employees with appropriate incentivization and compensation on their task and workload.

It is also important to note here that our results showed that *role ambiguity may not necessarily be "bad"*. It is possible that individuals who demonstrate desirable organizational characteristics, such as proactivity and initiative [27], may show high role ambiguity, simply because of their desire to self-present in a particular way. Therefore, we suggest caution in how `LibRA` is made actionable by companies, especially in the light of the many possibilities to build the above organization-centric technologies. We suggest that companies should not only encourage and provide rewards for these type of employees because they bring role and skill diversity to the organizational culture, but also consider shepherding these individuals with better coping strategies so that they deal better with their wellbeing concerns that are attributed to an underlying role ambiguity [86].

7.3 Social Computing Implications

Our work also has implications for *social computing system* design. Platforms such as LinkedIn cater to both individuals by recommending them jobs, as well as to companies by recommending them individuals. Their recommendation algorithms can leverage the quantified measure of role ambiguity (`LibRA`), complementing and going beyond general skills and experience matching. In addition, social computing platforms can aggregate role ambiguities between organizations, and within organizations across teams. This will add more transparency and objective information on company experiences, complementing the review websites (such as Glassdoor), which tend to be heavily polarized or biased on negative experiences [82]. These data sources will benefit both the job seekers as well as the employers in evaluating, understanding, and implementing measures to improve the work experience.

Finally, LinkedIn already enables individuals to gauge their "professional value" based on their profile stats [151]. An added feature to that could be a measure like `LibRA`, and guided recommendations on the basis of one's weaknesses (in terms of role ambiguity) to online training (such as Lynda[5]), or with classes at local third party training centers. For privacy-preserving purposes, LinkedIn anonymizes one's list of followers [151], but this also compounds the fact that there is no structured way to know "who sees what on Linkedin", adding complexity in terms of the audience is a problem that an individual faces [68, 91, 96]. However, the platform can adopt design changes such as allowing individuals with diversified interests to create multiple professional personas for different audiences. For example, someone who is both a Software Engineer as well as a part-time Physics Tutor, may self-promote their expertise and gain visibility in both the disciplines but to different controlled audiences [80], who can assess their role-related constructs only on the discipline that they are interested in.

7.4 Ethical, Privacy, Social, and Policy Implications

Back in 2014, when Zhang et al. studied "creepiness" and privacy concerns related to social media use by workplace professionals, they found concerns shifting from boundary regulation to behavior tracking by social media platforms for targeted advertising [163]. However, social media- and the web- based behavioral inferences has evolved tremendously since then, and also come under ethical and political scrutiny for privacy breaches such as the Cambridge Analytica scandal on Facebook [19]. Moreover, our work renews attention to the challenges that may arise when employee data is appropriated for workplace surveillance; as Van Dijck's research noted, "LinkedIn's functionality goes beyond its self-claimed ambition as a professional matchmaker, and ventures into behavioral monitoring." In fact, with research like ours, use of people's online self-presentation to infer their offline behavior (with high-risk decision outcomes such as one's profession or career) augments several complexities to one's perception of ethics and privacy, and consequently their behavior on social media. We discuss some of these challenges below.

Although our work leverages public social media of individuals, it raises new questions on the *privacy-breach of individual information*. An employee's motivations and expectations for LinkedIn might have been only to network or to browse jobs, and they may be well unaware that their published portfolio may also be used to analyze their present or future role-ambiguity and measures of organizational fit or job security [5, 31, 151, 163], which the individuals may not feel comfortable about, especially when this information is made accessible to their employers. Further, *this work is not intended to facilitate employer surveillance*, which shares a competing relationship with employee's subjective expectation of privacy [28, 51, 137].

More elaborately, per Goffman et al.'s theory of self-presentation, individuals may present two kinds of information — one that they intend to "give off", and one that "leaks through" without any intention [54, 102]. This implies that both of the perspectives may be present in our sort of research. Publishing role descriptions as online portfolios on public social media platforms like LinkedIn benefits the individuals in many ways, but research such as this may also abuse their data without their consent or awareness. For instance, employers may make inferences about role ambiguity and subsequent job satisfaction to make decisions on rewarding, promotions of employees, or even employee retention and layoffs. Therefore, to regulate such practices via the use of social media data, employee right protection agencies and lawmaking bodies such as the Department of Labor in the United States should consider making guidelines on how organizations engage in data-driven decision making regarding their workforce [73]. This work calls for constitutional jurisprudence in terms of employee social media rights and employer surveillance [51, 73].

Additionally, different companies have different kinds of expectations, history, culture, structure, and needs in their organizations that are latent and beyond what role descriptions say [43, 100, 132]. These factors, alongside platform-related and individuals' intrinsic factors that may impact their

[5] *linkedin.com/company/lynda-com/*, Accessed 2019-03-21

role ambiguity assessments, should be accounted for before making decisions merely on any sort of data-driven form of inferred role ambiguity.

On the contrary, *individuals may also start gaming the system*, and describe themselves in language that is more attuned with their role descriptions at work to gain professional advantages [151]. Such deceptive behavior calls for action for stakeholders with diverse interests ranging from academia and industry, as this adds complexities, and may even rigorously change the whole social computing ecosystem on LinkedIn compared to how it is used now. The platform may consider bringing moderation of content or user flair/karma (such as on Reddit) to enable that only credible information is shared on the platform. Presently, LinkedIn already includes features such as testimonials and recommendations that may be leveraged to counter such behavior on LinkedIn. However, such measures are biased as well and can cause Matthew Effect (*the rich get richer, and the poor get poorer*) [101], so accounting for them needs additional consideration.

In addition to the above, our work is only able to measure role ambiguities for those who are on LinkedIn, predominantly in white-collar jobs. According to Pew Survey Reports, 25% of U.S. adults are on LinkedIn, and the demographic is skewed towards the younger, urban, and college-graduate individuals [114]. It is likely that only "privileged" individuals can benefit from these kinds of online data- or technology- driven measures to advance and positively impact their job outcomes and wellbeing, e.g., via the self-reflection tools we discussed above. Consequently, those who are not on the platform (which could due to their socio-economic conditions, e.g., the vast majority of blue-collar job workers, or by choice), may feel compelled to use it owing to social and professional pressures of being on it. This adds to the complexities that prior work identified regarding *digital inequalities in job-seeking and job summarization behavior on the internet* [57, 76, 164].

7.5 Limitations and Future Directions

We recognize some limitations in this work. As mentioned, our approach of assessing role ambiguity applies to only those individuals who are on LinkedIn, and what individuals describe themselves on LinkedIn. Role ambiguity could be because of the role itself, or because of the inherent biases, intrinsic attributes, and online platform and self-presentation choices of the employees, as we noted in Section 6. Besides, the problem of honesty and deception on LinkedIn [60] remains underexplored, and should be accounted for when inferring data-driven workplace outcomes such as `LibRA`.

Our work is limited by the affordances and use-behavior of LinkedIn as a professional social networking platform. It is constrained by how updated the self-described portfolios of individuals are, and we only include a snapshot of LinkedIn profiles of individuals during the period of our study. However, an individual's role or perceived role in workplace is likely to change, and we do not account for any such internal changes or any internal communication that the management or the supervisors in the organizations may have made the employee aware about. Further, we note that causal inferences cannot be drawn based upon our study. Future work can involve experimental and quasi-experimental setting to study any sort of causal and temporal relationships of how role ambiguity, and LinkedIn profile update of individuals varies over time, and how does it affect their wellbeing, performance, and satisfaction in a workplace. Technically, our approach to quantify `LibRA` relies upon external sources of job description and manual inspection. Although such a process is challenging to be scaled, in practical scenarios such additional data can be obtained far more easily at low cost (both time and monetary) by the actual stakeholders and users of `LibRA` — individuals can use it against their own job descriptions, and organizations would have the repository of job descriptions to match against individuals, which are only periodically updated as new job titles are not created at rampant pace.

Despite using passively sensed wellbeing measures, this work suffers from the limitations as any other cross-sectional study that employs snapshots of data or self-reports at a point of time. Because we only study the relationship of `LibRA` with self-assessed job performance, we cannot make conclusive claims about its relationship with the employer or other stakeholders, such as supervisors-, peers-, and subordinates- assessed performance or rewarding at the workplace. Future research can model their studies on the cognitive model of stress that centers around repeating the cyclic process of appraisal, coping, and reappraisal [145].

8 CONCLUSION

This paper proposed a methodology to quantitatively estimate role ambiguity via unobtrusively gathered data from LinkedIn. Our dataset consisted of consented LinkedIn data of 267 information workers in the U.S. who are participants in a multimodal sensing study of job proficiency. We computed LinkedIn based Role Ambiguity (`LibRA`) as a difference in one's self-described roles (on LinkedIn) and the company-published job description of the same role. In particular, we measured these differences using word-embeddings on the multiple dimensions of job aspects across *abilities*, *interests*, *knowledge*, *skills*, *work activities*, *work context*, *work styles*, and *work values*. Aligning with a set of theory-driven hypotheses, we find that greater `LibRA` is associated with depleted wellbeing, such as increased heart rate, increased arousal, decreased sleep, and higher stress. In addition, `LibRA` is associated with lower job performance such as decreased organizational citizenship behavior and decreased task performance. Finally, we explored the self-presentation behavior and social computing platform-specific nuances and factors that need to be accounted if measures like `LibRA` are to be used in practice. This work can help fill gaps in state-of-the-art assessments of role ambiguity, and we discussed the potential of this measure in building novel technology-mediated strategies to combat role ambiguity, and improve efficiency in organizations.

9 ACKNOWLEDGMENTS

This research is supported in part by the Office of the Director of National Intelligence (ODNI), Intelligence Advanced Research Projects Activity (IARPA), via IARPA Contract No. 2017-17042800007. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of ODNI, IARPA, or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for governmental purposes notwithstanding any copyright annotation therein. We thank the entire Tesserae team for their invaluable contributions in realizing the goals of this project. We also thank Sindhu Ernala, Vedant Das Swain, Shagun Jhaver, Dong Whi Yoo, Stevie Chancellor, and the members of the Social Dynamics and Wellbeing Lab at Georgia Tech for their feedback.

REFERENCES

[1] David J Abramis and Long Beach. 2017. Work Role Ambiguity , Job Satisfaction , and Job Performance : Meta-Analyses and Review. February (2017). https://doi.org/10.2466/pr0.1994.75.3f.1411
[2] Peter Aldhous and Carol Dweck. 2008. Free your mind and watch it grow.
[3] Garmin Health API. 2018. http://developer.garmin.com/health-api/overview/. Accessed: 2018-11-01.
[4] Manager REST API. 2018. Employer Access to Employee Social Media: Applicant Screening, "Friend" Requests and Workplace Investigations. Accessed: 2018-11-01.
[5] Anne Archambault and Jonathan Grudin. 2012. A longitudinal study of facebook, linkedin, & twitter use. In *Proc. CHI*.
[6] James N Baron and William T Bielby. 1986. The proliferation of job titles in organizations. *Administrative Science Quarterly* (1986), 561–586.
[7] Murray R Barrick and Michael K Mount. 1991. The big five personality dimensions and job performance: a meta-analysis. *Personnel psychology* 44, 1 (1991), 1–26.
[8] Thomas S Bateman and J Michael Crant. 1993. The proactive component of organizational behavior: A measure and correlates. *Journal of organizational behavior* 14, 2 (1993), 103–118.
[9] Athanase Benetos, Annie Rudnichi, Frédérique Thomas, Michel Safar, and Louis Guize. 1999. Influence of heart rate on mortality in a French population: role of age, gender, and blood pressure. *Hypertension* 33, 1 (1999), 44–52.
[10] Michael S Bernstein, Eytan Bakshy, Moira Burke, and Brian Karrer. 2013. Quantifying the invisible audience in social networks. In *Proceedings of the SIGCHI conference on human factors in computing systems*. ACM, 21–30.
[11] Bruce J Biddle. 1986. Recent developments in role theory. *Annual review of sociology* 12, 1 (1986), 67–92.

[12] Mehrab Bin Morshed, Koustuv Saha, Richard Li, Sidney K. D'Mello, Munmun De Choudhury, Gregory D. Abowd, and Thomas Plötz. 2019. Prediction of Mood Instability with Passive Sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 3 (2019).
[13] Jessica M Blaxton, Cindy S Bergeman, Brenda R Whitehead, Marcia E Braun, and Jessic D Payne. 2017. Relationships among nightly sleep quality, daily stress, and daily affect. *The Journals of Gerontology: Series B* 72, 3 (2017), 363–372.
[14] Walter C Borman and SM Motowidlo. 1993. Expanding the criterion domain to include elements of contextual performance. *Personnel Selection in Organizations; San Francisco: Jossey-Bass* (1993), 71.
[15] Chieh-Chen Bowen, Janet K Swim, and Rick R Jacobs. 2000. Evaluating Gender Biases on Actual Job Performance of Real People: A Meta-Analysis 1. *Journal of Applied Social Psychology* 30, 10 (2000), 2194–2215.
[16] James A Breaugh and Joseph P Colihan. 1994. Measuring facets of job ambiguity: Construct validity evidence. *Journal of applied psychology* 79, 2 (1994), 191.
[17] Michael J Brzozowski. 2009. WaterCooler: exploring an organization through enterprise social media. In *Proceedings of the ACM 2009 international conference on Supporting group work.* ACM, 219–228.
[18] Ashley Buchanan and Margaret L Kern. 2017. The benefit mindset: The psychology of contribution and everyday leadership. *International Journal of Wellbeing* 7, 1 (2017).
[19] Carole Cadwalladr and Emma Graham-Harrison. 2018. Revealed: 50 million Facebook profiles harvested for Cambridge Analytica in major data breach. *The Guardian* 17 (2018).
[20] Ralf Caers and Vanessa Castelyns. 2011. LinkedIn and Facebook in Belgium: The influences and biases of social network sites in recruitment and selection procedures. *Social Science Computer Review* 29, 4 (2011), 437–448.
[21] Robert D Caplan and Kenneth W Jones. 1975. Effects of work load, role ambiguity, and type A personality on anxiety, depression, and heart rate. *Journal of applied psychology* 60, 6 (1975), 713.
[22] João Caramujo and Alberto Manuel Rodrigues da Silva. 2015. Analyzing privacy policies based on a privacy-aware profile: The Facebook and LinkedIn case studies. In *2015 IEEE 17th Conference on Business Informatics.*
[23] Raymond Bernard Cattell. 1987. *Intelligence: Its structure, growth and action.* Vol. 35. Elsevier.
[24] Stevie Chancellor and Scott Counts. 2018. Measuring Employment Demand Using Internet Search Data. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems.* ACM, 122.
[25] Esther Chang and Karen Hancock. 2003. Role stress and role ambiguity in new nursing graduates in Australia. *Nursing & health sciences* 5, 2 (2003), 155–163.
[26] Jose M Cortina and Joseph N Luchman. 2012. Personnel selection and employee performance. *Handbook of Psychology, Second Edition* 12 (2012).
[27] J Michael Crant. 2000. Proactive behavior in organizations. *Journal of management* 26, 3 (2000), 435–462.
[28] Melissa Crespo and Christine E Lyon. 2015. Employer Access to Employee Social Media: Applicant Screening, "Friend" Requests and Workplace Investigations. *Compliance, Employment Law, Privacy* (2015).
[29] Linda Crocker and James Algina. 1986. *Introduction to classical and modern test theory.* ERIC.
[30] Sauvik Das and Adam Kramer. 2013. Self-censorship on Facebook. In *Proc. ICWSM.*
[31] Vedant Das Swain, Manikanta D. Reddy, Kari Anne Nies, Louis Tay, Munmun De Choudhury, and Gregory D. Abowd. 2019. Birds of a Feather Clock Together: A Study of Person–Organization Fit Through Latent Activity Routines. *Proc. ACM Hum.-Comput. Interact* CSCW (2019).
[32] Robyn M Dawes and Bernard Corrigan. 1974. Linear models in decision making. *Psychological bulletin* (1974).
[33] Munmun De Choudhury and Scott Counts. 2013. Understanding affect in the workplace via social media. In *Proceedings of the 2013 conference on Computer supported cooperative work.* ACM, 303–316.
[34] Giada Di Stefano, Francesca Gino, Gary P Pisano, and Bradley R Staats. 2016. Making experience count: The role of reflection in individual learning. *Harvard Business School NOM Unit Working Paper* 14-093 (2016), 14–093.
[35] Richard A Dienstbier. 1989. Arousal and physiological toughness: implications for mental and physical health. *Psychological review* 96, 1 (1989), 84.
[36] Joan DiMicco, David R Millen, Werner Geyer, Casey Dugan, Beth Brownholtz, and Michael Muller. 2008. Motivations for social networking at work. In *Proc. CSCW.*
[37] Joan Morris DiMicco, Werner Geyer, David R Millen, Casey Dugan, and Beth Brownholtz. 2009. People sensemaking and relationship building on an enterprise social network site. In *2009 42nd Hawaii International Conference on System Sciences.* IEEE, 1–10.
[38] Judith S Donath et al. 1999. Identity and deception in the virtual community. *Communities in cyberspace* (1999).
[39] Carol S Dweck. 2009. Mindsets: Developing talent through a growth mindset. *Olympic Coach* 21, 1 (2009), 4–7.
[40] Kate Ehrlich and N Sadat Shami. 2010. Microblogging inside and outside the workplace. In *Fourth International AAAI Conference on Weblogs and Social Media.*
[41] Amir Erez, Vilmos F Misangyi, Diane E Johnson, Marcie A LePine, and Kent C Halverson. 2008. Stirring the hearts of followers: charismatic leadership as the transferal of affect. *Journal of applied psychology* 93, 3 (2008), 602.
[42] Rosta Farzan, Joan M DiMicco, David R Millen, Casey Dugan, Werner Geyer, and Elizabeth A Brownholtz. 2008. Results from deploying a participation incentive mechanism within the enterprise. In *Proceedings of the SIGCHI conference on Human factors in computing systems.* ACM, 563–572.

[43] Franco Fiordelisi and Ornella Ricci. 2014. Corporate culture and CEO turnover. *Journal of Corporate Finance* 28 (2014).

[44] James H Fowler and Nicholas A Christakis. 2008. Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *Bmj* 337 (2008), a2338.

[45] Suzy Fox, Paul E Spector, Angeline Goh, Kari Bruursema, and Stacey R Kessler. 2012. The deviant citizen: Measuring potential positive relations between counterproductive work behaviour and organizational citizenship behaviour. *Journal of Occupational and Organizational Psychology* 85, 1 (2012), 199–220.

[46] Bruno S Frey and Margit Osterloh. 2001. *Successful management by motivation: Balancing intrinsic and extrinsic incentives.* Springer Science & Business Media.

[47] Yitzhak Fried, Haim Ailan Ben-David, Robert B Tiegs, Naftali Avital, and Uri Yeverechyahu. 1998. The interactive effect of role conflict and role ambiguity on job performance. *Journal of occupational and organizational psychology* (1998).

[48] Adrian Furnham, Andreas Eracleous, and Tomas Chamorro-Premuzic. 2009. Personality, motivation and job satisfaction: Hertzberg meets the Big Five. *Journal of managerial psychology* 24, 8 (2009), 765–779.

[49] Alfonso Gambardella, Claudio Panico, and Giovanni Valentini. 2015. Strategic incentives to human capital. *Strategic Management Journal* 36, 1 (2015), 37–52.

[50] Werner Geyer, Casey Dugan, Joan DiMicco, David R Millen, Beth Brownholtz, and Michael Muller. 2008. Use and reuse of shared lists as a social content type. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.* ACM, 1545–1554.

[51] Saby Ghoshray. 2013. Employer surveillance versus employee privacy: The new reality of social media and workplace privacy. *N. Ky. L. Rev.* 40 (2013), 593.

[52] Eric Gilbert. 2012. Phrases that signal workplace hierarchy. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work.* ACM, 1037–1046.

[53] Erving Goffman. 1981. *Forms of talk.* University of Pennsylvania Press.

[54] Erving Goffman et al. 1959. The presentation of self in everyday life. (1959).

[55] Jeffrey L Goodie, Kevin T Larkin, and Scott Schauss. 2000. Validation of Polar heart rate monitor for assessing heart rate during physical and mental stress. *Journal of Psychophysiology* 14, 3 (2000), 159.

[56] Adam M Grant, Justin M Berg, and Daniel M Cable. 2014. Job titles as identity badges: How self-reflective titles can reduce emotional exhaustion. *Academy of Management journal* 57, 4 (2014), 1201–1225.

[57] Anne E Green, Yuxin Li, David Owen, and Maria De Hoyos. 2012. Inequalities in use of the Internet for job search: similarities and contrasts by economic status in Great Britain. *Environment and Planning A* 44, 10 (2012), 2344–2358.

[58] Mark A Griffin, Andrew Neal, and Sharon K Parker. 2007. A new model of work role performance: Positive behavior in uncertain and interdependent contexts. *Academy of management journal* 50, 2 (2007), 327–347.

[59] Xing Sam Gu and Paul R Rosenbaum. 1993. Comparison of multivariate matching methods: Structures, distances, and algorithms. *Journal of Computational and Graphical Statistics* 2, 4 (1993), 405–420.

[60] Jamie Guillory and Jeffrey T Hancock. 2012. The effect of Linkedin on deception in resumes. *Cyberpsychology, Behavior, and Social Networking* 15, 3 (2012), 135–140.

[61] Jamie Guillory, Jason Spiegel, Molly Drislane, Benjamin Weiss, Walter Donner, and Jeffrey Hancock. 2011. Upset now?: emotion contagion in distributed groups. In *Proc. CHI.* ACM.

[62] Anil K Gupta and Vijay Govindarajan. 2002. Cultivating a global mindset. *Academy of Management Perspectives* 16, 1 (2002), 116–126.

[63] Nina Haferkamp, Sabrina C Eimler, Anna-Margarita Papadakis, and Jana Vanessa Kruck. 2012. Men are from Mars, women are from Venus? Examining gender differences in self-presentation on social networking sites. *Cyberpsychology, Behavior, and Social Networking* 15, 2 (2012), 91–98.

[64] Juliane Hellhammer and Melanie Schubert. 2012. The physiological response to Trier Social Stress Test relates to subjective measures of stress during but not before or after the test. *Psychoneuroendocrinology* 37, 1 (2012), 119–124.

[65] Herbert G Heneman. 1974. Comparisons of self-and superior ratings of managerial performance. *Journal of Applied Psychology* 59, 5 (1974), 638.

[66] Louis Hickman, Koustuv Saha, Munmun De Choudhury, and Louis Tay. 2019. Automated tracking of components of job satisfaction via text mining of twitter data. In *ML Symposium, SIOP.*

[67] Joseph M Hilbe. 2011. *Negative binomial regression.* Cambridge University Press.

[68] Bernie Hogan. 2010. The presentation of self in the age of social media: Distinguishing performances and exhibitions online. *Bulletin of Science, Technology & Society* 30, 6 (2010), 377–386.

[69] Robyn Huff-Eibl, Jeanne F Voyles, and Michael M Brewer. 2011. Competency-based hiring, job description, and performance goals: The value of an integrated system. *Journal of Library Administration* 51, 7-8 (2011), 673–691.

[70] John E Hunter and Hannah Rothstein Hirsh. 1987. Applications of meta-analysis. (1987).

[71] Guido W Imbens and Donald B Rubin. 2015. *Causal inference in statistics, social, and biomedical sciences.* Cambridge.

[72] Susan E Jackson and Randall S Schuler. 1985. A meta-analysis and conceptual critique of research on role ambiguity and role conflict in work settings. *Organizational behavior and human decision processes* 36, 1 (1985), 16–78.

[73] Willow S Jacobson and Shannon Howle Tufts. 2013. To post or not to post: Employee rights and social media. *Review of public personnel administration* 33, 1 (2013), 84–107.

[74] Michal Jacovi, Ido Guy, Shiri Kremer-Davidson, Sara Porat, and Netta Aizenbud-Reshef. 2014. The perception of others: inferring reputation from social media in the enterprise. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*. ACM, 756–766.

[75] Shagun Jhaver, Justin Cranshaw, and Scott Counts. 2019. Measuring Professional Skill Development in U.S. Cities Using Internet Search Queries. In *ICWSM*.

[76] Shagun Jhaver, Sucheta Ghoshal, Amy Bruckman, and Eric Gilbert. 2018. Online harassment and content moderation: The case of blocklists. *ACM Transactions on Computer-Human Interaction (TOCHI)* 25, 2 (2018), 12.

[77] M Kahn, NP Barney, RM Briggs, KJ Bloch, and MR Allansmith. 1990. Penetrating the conjunctival barrier. The role of molecular weight. *Investigative ophthalmology & visual science* 31, 2 (1990), 258–261.

[78] Robert L Kahn and Philippe Byosiere. 1992. Stress in organizations. (1992).

[79] Robert L Kahn, Donald M Wolfe, Robert P Quinn, J Diedrick Snoek, and Robert A Rosenthal. 1964. Organizational stress: Studies in role conflict and ambiguity. (1964).

[80] Sanjay Kairam, Mike Brzozowski, David Huffaker, and Ed Chi. 2012. Talking in circles: selective sharing in google+. In *Proceedings of the SIGCHI conference on human factors in computing systems*. ACM, 1065–1074.

[81] Lynda A King and Daniel W King. 1990. Role conflict and role ambiguity: A critical assessment of construct validity. *Psychological Bulletin* 107, 1 (1990), 48.

[82] Nadav Klein, Ioana Marinescu, Andrew Chamberlain, and Morgan Smart. 2018. Online Reviews Are Biased. HereâĂŹs How to Fix Them. *Harvard Business Review (https://goo. gl/CZSa5B)* (2018).

[83] Donald E Klingner. 1979. When the traditional job description is not enough. *Personnel journal* (1979).

[84] Tanja Koch, Charlene Gerber, and Jeremias J de Klerk. 2018. The impact of social media on recruitment: Are you LinkedIn? *SA Journal of Human Resource Management* 16, 1 (2018), 1–14.

[85] Keely Kolmes. 2012. Social media in the future of professional psychology. *Professional Psychology: Research and Practice* 43, 6 (2012), 606.

[86] Jaana Kuoppala, Anne Lamminpää, Juha Liira, and Harri Vainio. 2008. Leadership, job well-being, and health effectsâĂŤa systematic review and a meta-analysis. *Journal of occupational and environmental medicine* 50, 8 (2008).

[87] Nicholas Ladany and Myrna L Friedlander. 1995. The relationship between the supervisory working alliance and trainees' experience of role conflict and role ambiguity. *Counselor Education and supervision* 34, 3 (1995), 220–231.

[88] Richard S Lazarus. 1995. Psychological stress in the workplace. *Occupational stress: A handbook* 1 (1995), 3–14.

[89] Jongseo Lee and Juyoung Kang. 2017. A Study on Job Satisfaction Factors in Retention and Turnover Groups using Dominance Analysis and LDA Topic Modeling with Employee Reviews on Glassdoor. com. (2017).

[90] Lu Luo. 1999. Work motivation, job stress and employees' well-being. *Journal of applied management studies* 8 (1999).

[91] Xiao Ma, Jeff Hancock, and Mor Naaman. 2016. Anonymity, intimacy and self-disclosure in social media. In *Proceedings of the 2016 CHI conference on human factors in computing systems*. ACM, 3857–3869.

[92] William H Macey and Benjamin Schneider. 2008. The meaning of employee engagement. *Industrial and organizational Psychology* 1, 1 (2008), 3–30.

[93] James Manyika, Susan Lund, Michael Chui, Jacques Bughin, Jonathan Woetzel, Parul Batra, Ryan Ko, and Saurabh Sanghvi. 2017. Jobs lost, jobs gained: Workforce transitions in a time of automation. *McKinsey Global Institute* (2017).

[94] Gloria Mark, Shamsi T Iqbal, Mary Czerwinski, and Paul Johns. 2014. Bored mondays and focused afternoons: The rhythm of attention and online activity in the workplace. In *Proc. CHI*. ACM, 3025–3034.

[95] Alice E Marwick. 2017. Entrepreneurial Subjects: Venturing from Alley to Valley. *International Journal of Communication (19328036)* 11 (2017).

[96] Alice E Marwick and Danah Boyd. 2011. I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New media & society* 13, 1 (2011), 114–133.

[97] Rebecca C Masson, Mark A Royal, Tom G Agnew, and Saul Fine. 2008. Leveraging employee engagement: The practical implications. *Industrial and Organizational Psychology* 1, 1 (2008), 56–59.

[98] Stephen M. Mattingly, Julie M. Gregg, Pino Audia, Ayse Elvan Bayraktaroglu, Andrew T. Campbell, Nitesh V. Chawla, Vedant Das Swain, Munmun De Choudhury, Sidney K. D'Mello, Anind K. Dey, Ge Gao, Krithika Jagannath, Kaifeng Jiang, Suwen Lin, Qiang Liu, Gloria Mark, Gonzalo J. Martinez, Kizito Masaba, Shayan Mirjafari, Edward Moskal, Raghu Mulukutla, Kari Nies, Manikanta D. Reddy, Pablo Robles-Granda, Koustuv Saha, Anusha Sirigiri, and Aaron Striegel. 2019. The Tesserae Project: Large-Scale, Longitudinal, In Situ, Multimodal Sensing of Information Workers. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems (CHI EA '19)*. https://doi.org/10.1145/3290607.3299041

[99] Joseph E McGrath. 1976. Stress and behavior in organization. Handbook of industrial and organizational psychology. *Chicago: RandMcnall* (1976).

[100] David E McNabb and F Thomas Sepic. 1995. Culture, climate, and total quality management: Measuring readiness for change. *Public Productivity & Management Review* (1995), 369–385.

[101] Robert K Merton. 1968. The Matthew effect in science: The reward and communication systems of science are considered. *Science* 159, 3810 (1968), 56–63.

[102] Hugh Miller. 1995. The presentation of self in electronic life: Goffman on the Internet. In *Embodied knowledge and virtual space conference*, Vol. 9.
[103] Shayan Mirjafari, Kizito Masaba, Ted Grover, Weichen Wang, Pino Audia, Andrew T Campbell, Nitesh V Chawla, Munmun De Choudhury, et al. 2019. Differentiating Higher and Lower Job Performers in the Workplace using Mobile Sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 1 (2019), 1–23.
[104] Tanushree Mitra and Eric Gilbert. 2012. Have you heard?: How gossip flows through workplace email. In *ICWSM*.
[105] Tanushree Mitra, Michael Muller, N Sadat Shami, Abbas Golestani, and Mikhil Masli. 2017. Spread of Employee Engagement in a Large Organizational Network: A Longitudinal Analysis. *PACM HCI* CSCW (2017).
[106] Stephan J Motowidlo and Harrison J Kell. 2012. Job performance. *Handbook of Psychology, Second Edition* 12 (2012).
[107] David A Nadler, G Douglas Jenkins, Cortlandt Cammann, and Edward E Lawler. 1975. The Michigan organizational assessment package: Progress report II. *Ann Arbor: Institute for Social Research, University of Michigan* (1975).
[108] Raymond A Noe, John R Hollenbeck, Barry Gerhart, and Patrick M Wright. 2017. *Human resource management: Gaining a competitive advantage.* McGraw-Hill Education New York, NY.
[109] Robert M O´brien. 2007. A caution regarding rules of thumb for variance inflation factors. *Quality & quantity* 41, 5 (2007), 673–690.
[110] Gary M Olson and Judith S Olson. 2000. Distance matters. *Human–computer interaction* 15, 2-3 (2000), 139–178.
[111] Dennis W Organ. 1988. *Organizational citizenship behavior: The good soldier syndrome.* Lexington Books/DC Heath and Com.
[112] Jone L Pearce. 1981. Bringing some clarity to role ambiguity research. *Academy of Management Review* (1981).
[113] Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*. 1532–1543.
[114] Pew. 2018. pewinternet.org/fact-sheet/social-media. Accessed: 2018-04-18.
[115] Bruce Louis Rich, Jeffrey A Lepine, and Eean R Crawford. 2010. Job engagement: Antecedents and effects on job performance. *Academy of management journal* 53, 3 (2010), 617–635.
[116] Kelsey-Jo Ritter, Russell A Matthews, Michael T Ford, and Alexandra A Henderson. 2016. Understanding role stressors and job satisfaction over time using adaptation theory. *Journal of Applied Psychology* 101, 12 (2016), 1655.
[117] John R Rizzo, Robert J House, and Sidney I Lirtzman. 1970. Role conflict and ambiguity in complex organizations. *Administrative science quarterly* (1970), 150–163.
[118] Maria Rotundo and Paul R Sackett. 2002. The relative importance of task, citizenship, and counterproductive performance to global ratings of job performance: A policy-capturing approach. *Journal of applied psychology* (2002).
[119] Koustuv Saha, Ayse Elvan Bayraktaraglu, Andrew Campbell, Nitesh V Chawla, Munmun De Choudhury, et al. 2019. Social Media as a Passive Sensor in Longitudinal Studies of Human Behavior and Wellbeing. In *CHI Ext. Abstracts*.
[120] Koustuv Saha and Munmun De Choudhury. 2017. Modeling Stress with Social Media Around Incidents of Gun Violence on College Campuses. *Proc. ACM Hum.-Comput. Interact.* 1, CSCW, Article 92 (Dec. 2017), 27 pages.
[121] Koustuv Saha, Manikanta D Reddy, Vedant Das Swain, Julie M Gregg, Ted Grover, Suwen Lin, Gonzalo J Martinez, Stephen M Mattingly, et al. 2019. Imputing Missing Social Media Data Stream in Multisensor Studies of Human Behavior. In *Proceedings of International Conference on Affective Computing and Intelligent Interaction (ACII 2019)*.
[122] Koustuv Saha, Manikanta D Reddy, and Munmun De Choudhury. 2019. JobLex: A Lexico-Semantic Knowledgebase of Occupational Information Descriptors. In *SocInfo*.
[123] Koustuv Saha, Benjamin Sugar, John Torous, Bruno Abrahao, Emre Kıcıman, and Munmun De Choudhury. 2019. A Social Media Study on the Effects of Psychiatric Medication Use. In *Proc. ICWSM*.
[124] Koustuv Saha, Ingmar Weber, and Munmun De Choudhury. 2018. A Social Media Based Examination of the Effects of Counseling Recommendations After Student Deaths on College Campuses. In *ICWSM*.
[125] Alan M Saks. 2006. Antecedents and consequences of employee engagement. *Journal of managerial psychology* (2006).
[126] Marcela Sapone. 2019. medium.com/@MsSapone/why-titles-will-kill-your-startup-58402c5b6954. Accessed: 2019-03-26.
[127] Susanne Schmidt, Ulrike Roesler, Talin Kusserow, and Renate Rau. 2014. Uncertainty in the workplace: examining role ambiguity and role conflict, and their link to depression – a meta-analysis. *European Journal of Work and Organizational Psychology* 23, 1 (2014), 91–106.
[128] Neal Schmitt, Jose M Cortina, Michael J Ingerick, and Darin Wiechmann. 2003. Personnel selection and employee performance. *Handbook of psychology: Industrial and organizational psychology* 12 (2003), 77–105.
[129] W Joel Schneider and Kevin S McGrew. 2012. The Cattell-Horn-Carroll model of intelligence. (2012).
[130] N Sadat Shami, Michael Muller, Aditya Pal, Mikhil Masli, and Werner Geyer. 2015. Inferring employee engagement from social media. In *Proc. CHI*.
[131] N Sadat Shami, Jeffrey Nichols, and Jilin Chen. 2014. Social media participation and performance at work: a longitudinal study. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 115–118.
[132] N Sadat Shami, Jiang Yang, Laura Panc, Casey Dugan, Tristan Ratchford, Jamie C Rasmussen, Yannick M Assogba, Tal Steier, Todd Soule, Stela Lupushor, et al. 2014. Understanding employee social media chatter with enterprise social pulse. In *Proc. CSCW*.

[133] Walter C Shipley. 2009. *Shipley-2: manual.* WPS.
[134] Jagdip Singh. 1993. Facets , Ambiguity :. *The Journal of Marketing* 57, 2 (1993), 11–31.
[135] Meredith M Skeels and Jonathan Grudin. 2009. When social networks cross boundaries: a case study of workplace use of facebook and linkedin. In *Proc. GROUP*. ACM.
[136] Carlla S Smith, John Tisak, and Robert A Schmieder. 1993. The measurement properties of the role conflict and role ambiguity scales: A review and extension of the empirical research. *Journal of organizational Behavior* (1993).
[137] Daniel J Solove. 2007. I've got nothing to hide and other misunderstandings of privacy. *San Diego L. Rev.* (2007).
[138] Christopher J Soto and Oliver P John. 2017. The next Big Five Inventory (BFI-2): Developing and assessing a hierarchical model with 15 facets to enhance bandwidth, fidelity, and predictive power. *Journal of Personality and Social Psychology* 113, 1 (2017), 117.
[139] Sherny E Sullivan and Rabi S Bhagat. 1992. Organizational stress, job satisfaction and job performance: where do we go from here? *Journal of management* 18, 2 (1992), 353–374.
[140] Roshan Sumbaly, Jay Kreps, and Sam Shah. 2013. The big data ecosystem at linkedin. In *Proceedings of the 2013 ACM SIGMOD International Conference on Management of Data*. ACM, 1125–1134.
[141] Prasanna Tambe and Lorin M Hitt. 2012. Now IT's personal: Offshoring and the shifting skill composition of the US information technology workforce. *Management Science* 58, 4 (2012), 678–695.
[142] Robert P Tett, Douglas N Jackson, and Mitchell Rothstein. 1991. Personality measures as predictors of job performance: A meta-analytic review. *Personnel psychology* 44, 4 (1991), 703–742.
[143] James D Thompson. 2017. *Organizations in action: Social science bases of administrative theory.* Routledge.
[144] Sigal Tifferet and Iris Vilnai-Yavetz. 2018. Self-presentation in LinkedIn portraits: common features, gender, and occupational differences. *Computers in Human Behavior* 80 (2018), 33–48.
[145] Allison S Troy, Frank H Wilhelm, Amanda J Shallcross, and Iris B Mauss. 2010. Seeing the silver lining: cognitive reappraisal ability moderates the relationship between stress and depressive symptoms. *Emotion* 10, 6 (2010), 783.
[146] Zeynep Tufekci. 2008. Can you see me now? Audience and disclosure regulation in online social network sites. *Bulletin of Science, Technology & Society* 28, 1 (2008), 20–36.
[147] Josh Tyler. 2015. The Myth of the Ninja Rockstar Developer. In *Building Great Software Engineering Teams.*
[148] Sonja Utz. 2016. Is LinkedIn making you more successful? The informational benefits derived from public social media. *New Media & Society* 18, 11 (2016), 2685–2702.
[149] Sonja Utz and Johannes Breuer. 2019. The Relationship Between Networking, LinkedIn Use, and Retrieving Informational Benefits. *Cyberpsychology, Behavior, and Social Networking* (2019).
[150] Niels van de Ven, Aniek Bogaert, Alec Serlie, Mark J Brandt, and Jaap JA Denissen. 2017. Personality perception based on LinkedIn profiles. *Journal of Managerial Psychology* 32, 6 (2017), 418–429.
[151] José Van Dijck. 2013. 'You have one identity': Performing the self on Facebook and LinkedIn. *Media, culture & society* 35, 2 (2013), 199–215.
[152] Olivier Van Reeth, Laurence Weibel, Karine Spiegel, Rachel Leproult, C Dugovic, and Stefania Maccari. 2000. Physiology of sleep (review)–interactions between stress and sleep: from basic research to clinical situations. *Sleep Medicine Reviews* 4, 2 (2000), 201–219.
[153] Mary Van Sell, Arthur P. Brief, and Randall S. Schuler. 1981. Role Conflict and Role Ambiguity: Integration of the Literature and Directions for Future Research. *Human Relations* 34, 1 (1981), 43–71.
[154] Chockalingam Viswesvaran and Deniz S Ones. 2000. Perspectives on models of job performance. *International Journal of Selection and Assessment* 8, 4 (2000), 216–226.
[155] Rui Wang, Fanglin Chen, Zhenyu Chen, Tianxing Li, Gabriella Harari, Stefanie Tignor, Xia Zhou, Dror Ben-Zeev, and Andrew T Campbell. 2014. StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones. In *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing*. ACM, 3–14.
[156] Jack W Wiley, Brenda J Kowske, and Anne E Herman. 2010. Developing and validating a global model of employee engagement. *Handbook of Employee Engagement: Perspectives, Issues, Research and Practice* (2010).
[157] Larry J Williams and Stella E Anderson. 1991. Job satisfaction and organizational commitment as predictors of organizational citizenship and in-role behaviors. *Journal of management* 17, 3 (1991), 601–617.
[158] Thomas A Wright and Douglas G Bonett. 2007. Job satisfaction and psychological well-being as nonadditive predictors of workplace turnover. *Journal of management* 33, 2 (2007), 141–160.
[159] Thomas A Wright and Russell Cropanzano. 2000. Psychological well-being and job satisfaction as predictors of job performance. *Journal of occupational health psychology* 5, 1 (2000), 84.
[160] Seokhwa Yun, Riki Takeuchi, and Wei Liu. 2007. Employee self-enhancement motives and job performance behaviors: Investigating the moderating effects of employee role ambiguity and managerial perceptions of employee commitment. *Journal of Applied Psychology* 92, 3 (2007), 745.
[161] Todd R Zenger. 1994. Explaining organizational diseconomies of scale in R&D: Agency problems and the allocation of engineering talent, ideas, and effort by firm size. *Management science* 40, 6 (1994), 708–729.
[162] Todd R Zenger and Sergio G Lazzarini. 2004. Compensating for innovation: Do small firms offer high-powered incentives that lure talent and motivate effort? *Managerial and Decision Economics* 25, 6-7 (2004), 329–345.

[163] Hui Zhang, Munmun De Choudhury, and Jonathan Grudin. 2014. Creepy but inevitable?: the evolution of social networking. In *Proc. CSCW*. ACM.
[164] Julie Zide, Ben Elman, and Comila Shahani-Denning. 2014. LinkedIn and recruitment: How profiles differ across occupations. *Employee Relations* 36, 5 (2014), 583–604.

Received April 2019; revised June 2019; accepted August 2019