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Social Media and Ubiquitous Technologies for Remote Worker Wellbeing and Productivity in a Post-Pandemic World

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***Abstract*—In light of the ongoing COVID-19 pandemic, remote work styles have become the norm. However, these work settings introduce new intricacies in worker behaviors. The overlap between work and home can disrupt performance. The lack of social interaction can affect motivation. This elicits a need to implement novel methods to evaluate and enhance remote worker functioning. The potential to unobtrusively and automatically assess such workers can be fulfilled by social media and ubiquitous technologies. This paper situates recent research in the new context by extending our insights for increased remote interaction and online presence. We present implications for proactive assessment of remote workers by understanding day-level activities, coordination, role awareness, and organizational culture. Additionally, we discuss the ethics of privacy-preserving deployment, employer surveillance, and digital inequity. This paper aims to inspire pervasive technologies for the new future of work.**

***Keywords*-COVID-19, future of work, remote work, social media, worker wellbeing, personnel management, routine, persona, role, culture, LinkedIn, Bluetooth, passive sensing**

I. Introduction

One of the most significant paradigm shifts in the workplace has been the emergence of mobile and internet technologies. For information work, the availability and accessibility of computing devices have allowed organizations to distribute productivity across workers [1]. Since then, the development in connectivity technologies and the ubiquity of intelligent devices in multiple environments has lead to flexible work options that expand beyond the built environment of the traditional workplace [2]. Workers could remain effective remotely and collaborate across geographically disparate locations and work settings. However, for most organizations these work methods had been auxiliary avenues to either support exceptional life-events (e.g., a family medical emergency) or accommodate specific job roles (e.g., consultancy). Today, the global pandemic due to the coronavirus disease (COVID-19) has brought about a new paradigm shift that has forced many organizations to embrace remote work as the new normal and not just a supplementary work style to accommodate atypical circumstances [3]. Although COVID-19 may be a transitory crisis and these remote work styles may be argued to dwindle away as the society returns to the pre-COVID-19 normal, many organizations are considering if this paradigm may be viable in the longer term, to support flexibility to less advantaged workers as well as promote inclusivity in the workforce. Twitter, for instance, has announced that its employees, if they desire, will be allowed to work remotely forever, even after the pandemic is over [4].

Two decades ago, Olson and Olson studied "distance matters" in workplaces, i.e., workers are much better engaged and performing when they are physically collocated than if they are remote. In the same vein, when the majority of the workforce is spatially distributed, organizations lose regular supervision of workers, making it challenging to evaluate worker needs [6]. Therefore, organizations need to consider new ways to assess, support, and improve worker performance and wellbeing. Manual evaluation of workers has limitations of scaling and subjective biases [7, 8, 9]. The backdrop of a pandemic and remote work may also increase the challenges of conducting such evaluations that require face-to-face physical interactions [10]. This has been the key motivation to explore pervasive technologies to understand worker outcomes in unobtrusive and automatic ways [11, 12, 13, 14, 15, 16, 17, 18]. This new future of work thus draws on many years of effort in the computer supported cooperative work (CSCW) and human-computer interaction (HCI) community towards augmenting worker collaboration, coordination, and engagement [19, 20, 21, 22]. The changing circumstances and work settings call for rethinking how to adapt these technologies for better assessing and understanding of worker behavior.

This paper contextualizes the potential of leveraging pervasive technologies for this new work paradigm to enable new forms of personnel management. Pervasive technologies include ubiquitous technologies such as wearables, bluetooth, and smartphone based sensors, as well as online technologies such as social media and crowd-contributed online platforms — these technologies have shown significant promises for passively understanding wellbeing both longitudinally and at scale [13, 21, 23, 24, 25, 26, 27, 28, 29, 30]. In particular, we draw on some of our recent work to discuss how they can be reconsidered and adapted. These include, 1) incorporating temporally-varying dynamic activities and going beyond static personality-based assessments,

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2) understanding worker coordination and routine amidst social distancing and absence of physical collocation, 3) inferring role awareness and adjusting role requirements, and 4) assessing work culture by leveraging crowd-contributed employee experiences. We conclude by discussing some of the major challenges and risks that may be exerted in deploying these technologies, such as the complexities of employer surveillance and digital divide in technology access.

II. Moving Beyond Static Personality: Incorporating Temporally-Varying Activity

Personality has been one of the most robust constructs to forecast job performance and other work-related outcomes [31, 32]. Depending on the nature of work, personality traits in themselves can predict a worker's functioning (e.g., high conscientiousness reflects the propensity to be orderly and responsible in any situation [33, 34], while high extraversion is considered favorable for client-facing roles [34]. The Asendorpf–Robins–Caspi (ARC) typology [35] describes that certain configurations of personality traits are more desirable. For instance, individuals typified as "resilient" are considered role models because of their adaptability [36]. In contrast, individuals described as the "undercontrolled" type are relatively antisocial, thus making their anticipated work functions less desirable [35]. Since personality is less sensitive to change, one could argue that remote settings would not disrupt worker functioning. However, personality alone does not entirely explain worker outcomes. This idea was originally postulated by theoretical frameworks that incorporate a worker's dynamic activities [37, 38]. Therefore, organizations require methods to evaluate how situational differences explain worker performance beyond what their personality can describe.

Advancement in passive technologies has found evidence that a worker's temporally-varying (e.g., day-level) activities are indeed associated with their performance. A survey of worker's physical movement has found that higher movement is related to an increase in task satisfaction and creative thinking [39]. In comparison to a workplace, work-from-home provides fewer natural opportunities to move (e.g., meetings in different floors, coffee and lunch breaks, or collaborating at a colleague's desk). Such behaviors can be automatically sensed with the help of passive sensors in worker devices (e.g., smartphones and workstation logs) [28]. Proximity sensors have been deployed in workspaces to investigate the importance of movement or more specifically the diversity in workspaces [40]. Therefore, organizations have an incentive to promote physical movement and suggest workers to change work locations. While the home setting might reduce mobility it also increases virtual communication. In fact, prior work has shown that a worker's approach to interacting with email can reflect their task performance and stress level [41]. Since the COVID-19 pandemic has forced an increased virtual communication overhead, organizations need to consider its effects on their worker outcomes. These findings motivate new hypotheses related to physical and communication activity that can be investigated through pervasive technologies a worker interacts with.

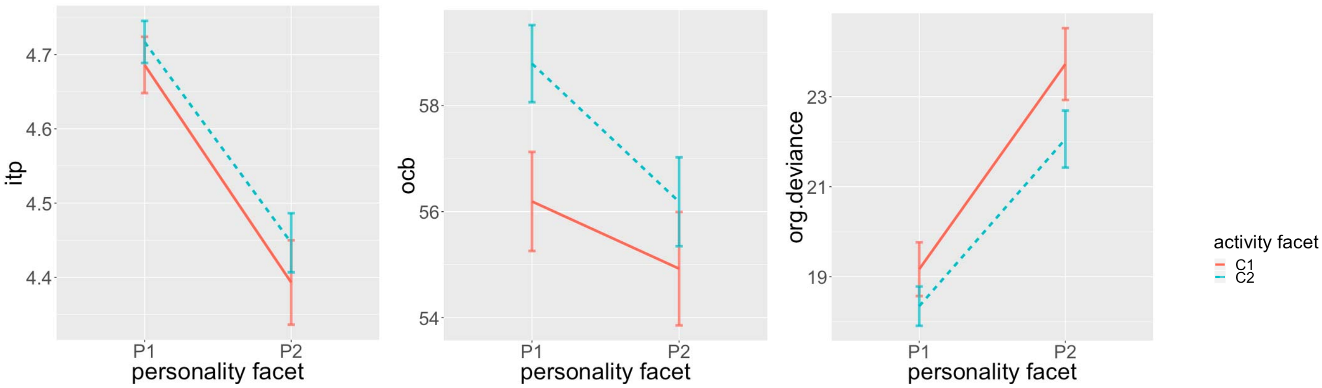
Despite findings that worker activities are related to their work experience, it is worth inquiring if this cannot be predicted by their personality. After all, it is much more convenient to deploy a one-time personality assessment. However, Das Swain et al. have shown that a worker's day-level activities explain their performance above and beyond their personality [18]. In this work, the authors used activity logs from smartphones, wearables and bluetooth beacons to distinguish its effects from the workers' personality. Particularly, in their dataset, workers who batch their phone use, spend shorter sessions at their desk, and sleep more performed better irrespective of their personality being "resilient" or "undercontrolled" (Figure 1). Not only does an understanding of day-level activity make studies of performance more comprehensive, for certain metrics such as *Organizational Citizenship Behavior* — often referred to as *Contextual Performance* — day-level activities explain approximately 50% variance [18].

> While personality changes steadily, day-level activities are sensitive to disruptions in the work context, such as an extended stay-at-home protocol in the light of the COVID-19 pandemic. Therefore, personnel management should leverage data from worker devices to identify mutable activities associated with better performance [18, 40] and promote positive activities and behaviors within the workforce.

III. Methods to Infer Workplace Coordination

Enforcing social distancing is considered to be an effective protocol to curtail the spread of contagious diseases [43]. Ironically, "social distance" refers to maintaining physical distance from others even though individuals still remain socially connected through alternative means. As a result, workers are expected to continue collaborating and communicating within their teams. However, since complying to stay-at-home requirements restricts collective presence at the workplace, it also restricts how a worker interacts with their colleagues and peer. For example, Olson and Olson have stated that "spatiality"— or presence in the company of teammates— is salient to successful collaboration among workers even when they do not verbally communicate [5]. Pervasive technologies have shown empirical evidence that supports the importance of coordination on worker performance [42, 44, 45].

Olguín et al. used wearables to show that social interactions in physical proximity of peers explain job satisfaction [46]. Similarly, association logs on a campus WiFi



(a) ITP (b) OCB (c) Org.Deviance

Figure 1: Main effects of personality and activities on task performance (itp), citizenship behavior (ocb), and organizational deviance (od). P_1 is equivalent to "resilient" personality type and scores better on all metrics. C_2 represents specific day-level activities, and rates better on all metrics, published in Das Swain et al. [18]

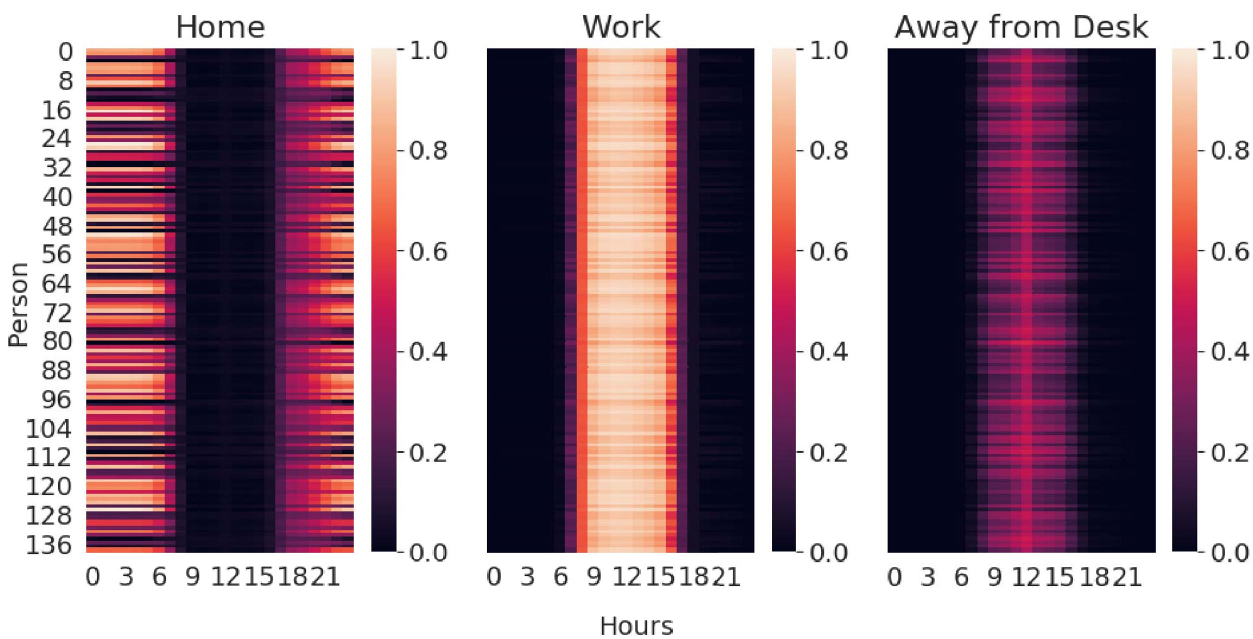


Figure 2: Logging behaviors, such as the time of away from the desk, can help reveal latent routines within an organization (e.g., most people are not at their desk during noon). Complying with these latent patterns are related to positive performance outcomes, as published in Das Swain et al. [42]

network can reveal if groups are working together [47]. While presence in the physical proximity matters, it is now a luxury amidst social distancing. This motivates the need to uncover implicit forms of interaction between workers that are not as explicit as face-to-face or physically collocated interactions. In light of this, synchrony in worker routines has been found to capture latent behaviors of coordination — and by extension *person–organization fit* [42]. Das Swain et al. found that when the pattern in which workers spend time away from their desk is similar to their cohort's pattern (Figure 2) it is associated with increased performance [42]. In the current setting of the COVID-19 pandemic, this approach can be extrapolated to a worker's desktop activity and their calendar schedule to learn *fit* with their cohort, i.e, how "in-sync" or coordinated they are [42]. In fact, studies on open-source software communities reveal that synchrony in crowd code contribution helps codebases evolve [45]. Overall, this presents an opportunity to study social interactions through virtual interfaces.

The pre-pandemic setting allowed workers to be aware of their cohort's behaviors by being in the same physical space. In a remote setup that may extend to situations well past the pandemic is over, designers of workplace technology should consider ways to reveal aggregate cohort behaviors so that workers can calibrate both work and break sessions. Normalizing one's routine to their peers can help coordination and thus support both performance and wellbeing [42].

IV. Novel Approaches for Understanding Job Roles

The well-approved "Role Theory" posits that an individual's workplace productivity and wellbeing is significantly moderated by the complexities, awareness, and expectations associated with one's *role* within and beyond an organization's boundaries [49, 50]. The discrepancy between *what an employer expects* and *what an employee does* at the workplace is called as *role ambiguity*. It includes uncertainties relating to role definition, expectations, responsibilities, tasks, and behaviors involved in one or more facets of task environment [50, 51, 52]. Traditionally, role ambiguity is measured using survey instruments recording employees' perceived clarity of assigned tasks and expectations on the tasks and peers [53]. As a step towards addressing the challenges of these approaches (subjective bias, limited to "perceived" component of role ambiguity, etc.) by using complementary information, Saha et al. leveraged LinkedIn data to compute LinkedIn based Role Ambiguity (`LibRA`) [48]. This work used natural language analysis to operationalize `LibRA` as the lexico-semantic difference between people's self-described LinkedIn portfolios and their company-provided job descriptions. Aligning with the role theory, this study found that greater `LibRA` measure is associated with depleted wellbeing and lower job performance.

With less of offline and physical interactions, approaches such as `LibRA` can be useful with both organization-centric and individual-centric implications. Work-from-home like settings will impact the scope to interact with colleagues. This might also make it harder for employees to self-evaluate themselves in the context of their team and collaborations, and be aware of peer expectations. At the same time, with the lack of physical and coordinated group interactions, organizations will find it harder to assess role matching of employees. However, remote work settings may lead to greater pervasiveness of people's online self-presentation of professional portfolios on both internal and external online portals, providing an increased opportunity for the success of unobtrusive online data-driven assessment [48, 54, 55]. Metrics like `LibRA` can be used to design self-reflection tools that allow employees to continually assess and understand their role ambiguities and match their skillset and productivity with employer expectations. From an organizational standpoint, Saha et al. [48] show example visualizations such as in Figure 3 that can help glean employee role ambiguity across job aspects [56]. Other work provided methodologies to continuously gauge employee pulse and employee affect [21, 23, 57]. Dashboards providing this kind of insights to human resources and personnel management teams, can be immensely helpful in proactive support and informed decision making in organizations.

Role constructs can be assessed with people's self-presentation on online professional portfolios [48]. Role ambiguity is not dependent on individual differences such as personality, gender, supervisory role, and executive function [58]. Importantly, diminished performance or wellbeing should not be blindly blamed on the employee's traits and abilities, but need to be introspected with additional awareness about their roles. Instead, companies need to carefully develop and adapt their job descriptions more attuned to the employees and the circumstances (e.g., ramifications and constraints related to COVID-19) [59, 60].

V. Evolution of Culture with Changing Work Settings and Practices

Organizational culture embodies a core value system which affects the development and execution of new ideas, and the management of unexpected events like crises [62, 63]. Organizational culture is both an indicator and a factor to influence its effectiveness [64]. Going beyond traditional approaches of quantifying organizational culture [65, 66, 67, 68, 69], research has assessed organizational culture by harnessing employees' naturalistic experiences shared on a variety of social and online media, including emails and internal communication channels [70, 71, 72, 73, 74]. In a recent work, Das Swain et al. [61] proposed a mechanism to leverage large-scale crowd-contributed employee experiences shared on Glassdoor to measure organizational culture by organizational sectors.

By definition, organizational culture is built on the premise that "people make the place". However, traditional definitions of "place" do not hold in remote work settings, essentially eliminating the element of physically collocated workers. This brings in new complexities and calls for rethinking the definition and assessment of organizational culture. While physical and environmental factors are minimized, norms and principles inherent in work practices in an organization (or a team) carry over in remote work settings as well.

Disruptions in normative workplace practices can cause a multitude of changes in organizational culture [75]. Das Swain et al. [61] operationalized organizational culture

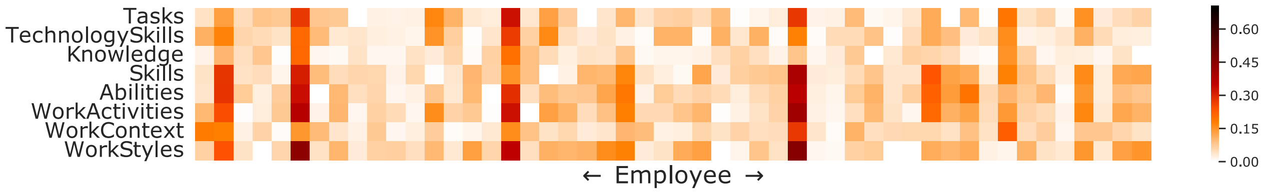


Figure 3: A visualization to compare and contrast `LibRA` by job aspect (y-axis) and employees (x-axis) as published in Saha et al. [48].

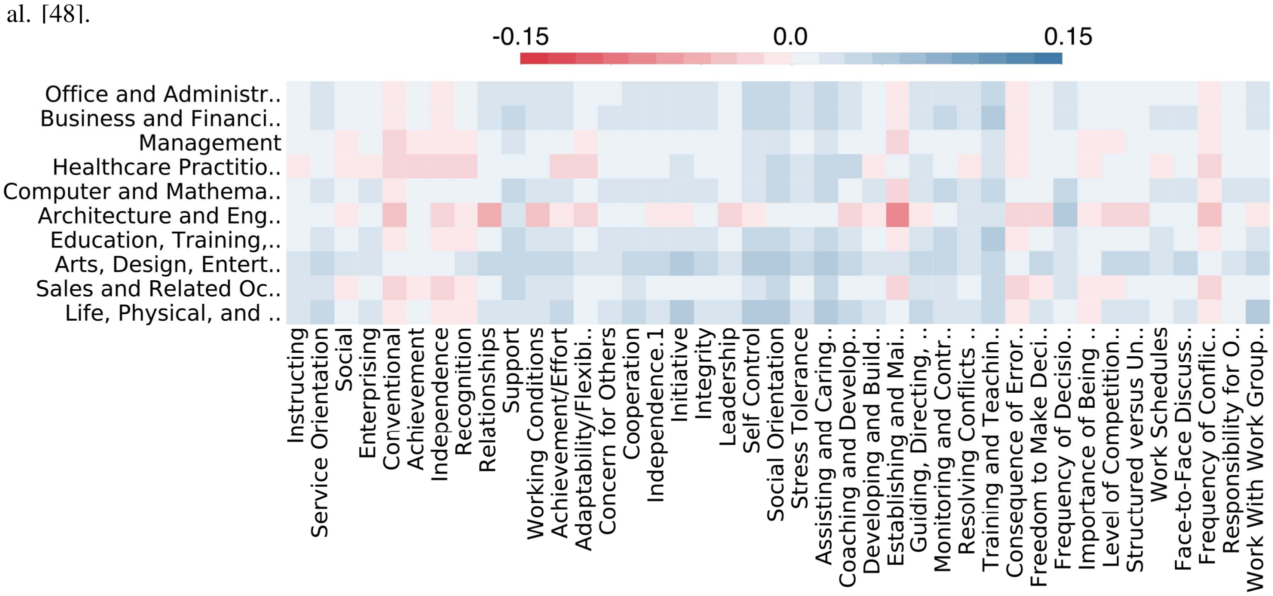


Figure 4: Organizational culture per organizational sector in a company by using employee experiences' data from Glassdoor, as published in Das Swain et al. [61].

as a multi-dimensional construct cutting across job dimensions of interests, work values, work activities, social skills, structural job characteristics, work styles, and interpersonal relationships [61]. Figure 4 shows an example visualization of culture per job dimension across different sectors in an organization [61]. By adopting such assessments in a continuous fashion over time will allow organizations to glean the evolving nature of their culture and conduct timely and tailored interventions to enhance employee wellbeing. For example, the same work found "work-life balance" to be one of the predominant concerns related to organizational culture, and COVID-19 disruptions can only reinforce complexities related to work-life balance [76], which need to be understood and addressed.

As workers adapt to the "new normal" subject to COVID-19 and possibly beyond, insights drawn out of culture assessments can help companies in restructuring work practices, schedules, and accommodating overlapping personal and professional workspaces in daily lives of people. Further, newer components of organizational culture can become prominent, or certain components can transcend into their online analogs. For example, "toxic work environments" can translate into remote and online interaction settings [77, 78].

VI. Ethical Implications for Pervasive Assessments of Remote Work

Operating unobtrusive technologies to evaluate employee behavior in the workplace has always been considered problematic [79, 80]. Many workers find it concerning that organizations are authorized to monitor large volumes of data from multiple data streams [79]. In the ongoing and ensuing post-COVID-19 world, such perceptions can be exacerbated by irresponsible implementation of the technologies to the new (remote) “workplace”, which cannot be distinguished from the home. Since it is challenging to discern this boundary, organizations risk enforcing worker’s total surveillance throughout the day [81]. In the new work setting, a misstep can not only violate the privacy of the worker, but also of other family members and occupants of their home. Therefore, to operate such applications, organizations need to not only request explicit consent but also weave privacy-preserving features into the design of their technologies.

Privacy by Design: These technologies should purposefully make it apparent to a worker what data is being collected, for how long it will be stored, and for what purpose [82]. This will provide workers the agency to regulate both their behaviors and the use of work systems.

Differential Privacy: The collected data should be obfuscated to make it non-trivial to identify workers [83]. This is particularly useful for many applications that study aggregate behaviors.

Another new challenge remote work presents is related to the unstructured nature of the new work environment. Various frameworks describe the effect of ecology on human behavior [37, 38]. Research in organizational behavior has extensively studied the *spillover effect* of home-to-work and work-to-home [84, 85]. Yet, the separation between home and work presented a somewhat consistent, predictable, and controllable ecology. However, in today’s remote setting, the variability in the environments has increased with the blurring between home and work [86]. Different workers have different family setups they need to accommodate, such as caring for their children or sharing devices with family members. In light of this, automated technologies to explain worker functioning can be vulnerable to over-generalize because it ignores the specifics of worker circumstances. This elicits the need to design person-centric approaches to infer worker experiences from data.

Person-Centric Applications: Since each worker is different, the changes to their context impact them differently. Therefore, these applications should view workers as an “integrated totality” by incorporating aspects of their life that cannot be passively sensed [87].

Lastly, technologies to augment remote work will disproportionately support those who can perform remote work. Within large organizations, the work force will include certain individuals who do not have the privilege of working-from-home effectively. This digital divide and related inequity in technology access will bias sway the benefits of social and ubiquitous technologies to those who have access to them. This raises questions regarding the representation of workers in digital data, particularly disadvantaging already underrepresented and marginalized groups in the workforce, such as women, LGBTQ+ individuals, racial and ethnic minorities, and people with disabilities. Before implementing such technologies, personnel management teams within organizations, therefore, need to be cognizant of who gets excluded from the data that informs their decisions. Subsequently, organizations should promote alternative means to gather those workers’ viewpoints as a collateral source of information and to thereby promote greater inclusivity.

Worker Representation: Any workplace technology alone will be biased to those with access. Therefore, organizations need to devise alternative means of leveraging workers’ perceptions that are ignored by the system. This encourages fortifying automatically collected data with other sources of information to equally represent the workers in decisions.

> Employer surveillance and employee’s subjective expectation of privacy share a competing relationship [88]. Only a thin line of difference exists in perceiving the same technology as *for surveillance* or *for assessment and wellbeing facilitation*. The potential risks and benefits, in light of a remote workforce in a post-COVID-19 world, need to be carefully evaluated before algorithms making inferences about offline critical outcomes (such as workplace assessments) are used in practice.

VII. Conclusion

The ongoing COVID-19 pandemic has disrupted personal, societal, and professional lives in a variety of ways. Disruptions include changes in work settings such as moving from physically collocated workplaces to remote settings. Likely, based on the work-from-home policies being increasingly adopted by many organizations in the aftermath of this pandemic, remote work styles may become more of a norm than an arrangement to accommodate atypical circumstances. In this shifting landscape of the future of work, we revisited some of our recent work that could be adapted for facilitating better personnel management and worker wellbeing going forward with changing work paradigm. This position article focused on employing social media and ubiquitous technologies for understanding day-level activities, worker coordination, role awareness, and organizational culture. We discussed how disrupted work settings might bring in new complexities in worker behavior, and how the novel assessments can facilitate tailored and timely support to address worker wellbeing and productivity concerns. Finally, we discussed how these technologies deployed to promote remote work styles bring in new ethical and privacy-related complexities surrounding employer surveillance, employee privacy, and digital divide, which need to be carefully considered when these technologies are put into practice.

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