A Survey of Passive Sensing in the Workplace

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Abstract—As emerging technologies increasingly integrate into all facets of our lives, the workplace stands at the forefront of potential transformative changes. A notable development in this realm is the advent of passive sensing technology, designed to enhance both cognitive and physical capabilities by monitoring human behavior. This paper reviews current research on the application of passive sensing technology in the workplace, focusing on its impact on employee wellbeing and productivity. Additionally, we explore unresolved issues and outline prospective pathways for the incorporation of passive sensing in future workplaces.

I. INTRODUCTION

With the growing adoption of technologies in the workplace, research on the “Future of Work” is intensively exploring ways to intelligently redesign workspaces. The goal is to enhance the talents of the workforce, both those recorded on and off the balance sheet. Among the rapidly growing technologies, passive sensors stand out for their ability to seamlessly integrate into work environments. These sensors collect data in situ without necessitating active engagement from individuals, facilitating a non-intrusive and pervasive means of understanding and supporting workers [1]. Through the passive collection of data, these technologies offer nuanced insights into worker behavior, allowing for empirical, contextually grounded analyses. Researchers have drawn links between passive sensing data and various behavioral markers, including mental wellbeing [2], personality traits [3], and productivity levels [4]. In the realm of the Future of Work, such technologies are invaluable for examining workers’ experiences both within and beyond the workplace over extended periods and at a broad scale. This is particularly relevant when traditional methods of evaluating worker performance and satisfaction—relying on self-reports or assessments from colleagues and supervisors—may fall short. The objective data collected from passive sensing technologies signals the emergence of innovative, hands-off approaches to assessing work dynamics.

We present a survey of existing research on the use of passive sensing technologies in the workplace to assess and promote wellbeing and productivity of the workforce. In this work, we consider “workplace” as the setting or place of employment where individuals perform tasks for their employer without regards to whether the space is private or shared. The results point out open problems and possible future directions in the field and suggest challenges to furthering the Future of Work using passive sensing technologies.
II. SURVEY METHODOLOGY

To ensure the relevance and rigor of our research, we conducted searches for terms like “passive sensing & future of work”, “wearables & worker productivity”, and “wearables & employee health”, leading us to review over 25,000 articles on platforms like Google Scholar. Our selection criteria favored recent papers published since 2015, including some seminal earlier works, and prioritized publications with a Google h5 index of 20 or higher. Furthermore, we imposed specific conditions to refine our focus. Studies had to involve the actual workforce engaged in day-to-day job activities, excluding simulations with non-working groups, such as students in office environments. The technologies considered had to be genuinely passive—unobtrusive, portable, and comfortably integrated into daily routines without requiring active interaction. The technologies should blend with the workers’ routine, rather than the workers changing their everyday routine to satisfy the study requirements. Therefore, research utilizing intrusive devices like EEG headsets, chest straps, gaze trackers, cameras and other cumbersome scientific devices was excluded in favor of those using more discreet and workplace-appropriate technologies. We focus on devices that we expect to have a higher acceptance in the office environment. This stringent selection process allowed us to accurately portray the state-of-the-art developments, progress, and hurdles in this field, providing a foundation to stimulate and guide further research on passive sensing technologies in the workplace.

III. PASSIVE SENSING

As ubiquitous devices become more embedded in our lives, they offer an unprecedented ability to passively capture our daily behavior at a high resolution via multiple sensors. Researchers have been leveraging passive sensing techniques to model users’ behavior and their environment from various perspectives. Before the emergence of smartphones and wearable devices, sensors built in cell phones (such as GPS and Bluetooth) were employed to passively sense users’ context. RealityMining [5] uses location signals and Bluetooth log data to recognize social patterns in daily user activity, identify socially significant locations and model organizational rhythms. CenceMe [9] uses a wider range of sensors – including embedded cameras, microphones, accelerometer, GPS, temperature, light, humidity, magnetometer and button clicks – to detect users’ activities and habits and injected these into popular social networking applications to promote social interaction. In addition to capturing personal behavior, passive sensing devices at a large scale enable people-centric urban sensing. MetroSense [7] combines mobile sensors (carried by people) and static sensors (installed among a city) to establish a large-scale passive sensing network that could support a wide variety of applications such as enterprises and hospitals. Recently, the advancement of mobile and wearable technology has further enhanced the capability of ubiquitous devices through longitudinal passive sensing. For example, StudentLife [2] uses smartphones to track college students’ daily behaviors for more than two months to assess their mental health, academic performance and behavioral trends.

Passive sensing is increasingly involved in various aspects of our daily lives. Within the workplace, it has been used to monitor physiological factors of workers, promote work safety, enhance efficiency among other things [8]. Recently, the Tesserae [9] project involved over 700 information workers to investigate how such technologies can be leveraged to measure workplace performance such as organizational citizenship behavior, as well as psychological traits and physical characteristics. In the rest of the article, we focus on applications of passive sensing technologies in the workplace to assess wellbeing and productivity of the workforce as the transition to the Future of Work takes place.

IV. UNDERSTANDING WORKPLACE DYNAMICS: INSIGHTS FROM PASSIVE SENSING ON WELLBEING AND PRODUCTIVITY

In this section, we examine the pivotal role of passive sensing technologies in deepening our understanding of workplace wellbeing and productivity. Through an examination of recent research studies, we highlight how these innovative tools offer important insights into the complex interplay between work environments and employee behavior. This exploration sheds light on the potential of passive sensing to optimize workplace dynamics and underscores its significance in fostering a more productive and health-conscious work culture.

A. WELLBEING

Over the years, there has been an increase in studies that explore the sensing capabilities of smartphones and wearables to assess as well as improve worker’s health and wellbeing. Among the papers selected, mental health issues such as stress, anxiety, affects are important dimensions studied. Most of these studies ask participants to self-report their health and wellbeing using validated instruments. While some studies use one-off survey scores, others employ experience sampling to study worker’s wellbeing in a longitudinal fashion. We list the key studies in Table I.

Assessing workers’ stress and/or anxiety is perhaps the most studied topic about worker’s wellbeing. As stress and anxiety are known to have an impact on heart rate (HR), most of the studies rely on HR-based signals obtained from wrist-worn wearables that employ photoplethysmography (PPG) [45] sensors. For instance, Feng et al. [10] show that PPG based HR and step counts from a Fitbit can be used to classify the anxiety level of nursing professionals. The authors introduce a pipeline for discovering behavioral consistency features, the inclusion of which leads to an overall improvement in the predictive model, with an accuracy of about 58%. For this work, the authors use the median-splitted score of self-reported State-Trait Anxiety Inventory (STAI) [46] as the ground truth. Similarly, in a study of 10 construction workers, Jebelli et al. [11] use a wrist wearable capable of not only capturing the participant’s HR through PPG signals, but also their electrodermal activity (EDA) and peripheral skin temperature...
TABLE I
STUDIED BEHAVIOR AND SENSORS USED. THE FOLLOWING TABLE LISTS ALL THE BEHAVIORS STUDIED IN THE PAPERS WE SURVEYED AND THE CORRESPONDING SENSOR DATA USED.

| Studied behavior       | Sensor/data                                                                 |
|------------------------|-----------------------------------------------------------------------------|
| Stress/anxiety         | HR, step count [10], HR, electrodermal activity, skin temperature [11], HR, email, calendar, time [12], Skin conductance, skin temperature, acceleration [13], workplace behavioral logs/ computer activity [14], [15], HR, stress, physical activity, context, user state, phone usage, Bluetooth [16], HRV, step count, sleep, acceleration, fat burn, cadence, breathing depth, sitting time, Bluetooth [17] |
| Sleep                  | HR, sleep duration, sleep efficiency [19], phone usage, movement, HR [20], HR, stress, physical activity, context, user state, phone usage, Bluetooth [21] |
| Affect/mood            | Skin conductance, skin temperature, acceleration [13], HR, step count, sleep [17], Sleep, activity duration [21], [22], computer activity [22], speech activity, Bluetooth [23], HR, stress, physical activity, context, user state, phone usage, Bluetooth [16], [24], physical activity, HR, skin response, skin temperature, respiration [25], HR, pulse, PPG, ECG, accelerometer, skin temperature [26], Sleep [27] |
| Focus/awkeness         | Physical activity, HR, skin response, skin temperature, respiration [25], Computer activity [28] |
| Productivity           | Computer activity [22], [29]–[31], Speech, calendar [30], Sleep [27] |
| Task performance       | HR, step count, Bluetooth [32], Bluetooth [33], HR, step count, sleep [17], Physical activity, speech activity, face to face interaction, proximity [34], Distance, location, still duration, sleep duration, sleep dept, phone usage, desk sessions [35], HR, stress, physical activity, sleep, phone usage, Bluetooth [36] |
| Citizenship behavior   | HR, stress, physical activity, sleep, phone usage, Bluetooth [4], HR, step count [10], [17], Distance, location, still duration, sleep duration, sleep dept, phone usage, desk sessions [35], Commute based physiology, weather, commute duration, commute variability [36] |
| Deviance               | HR, step count, Bluetooth [32], HR, step count [10], [17], HR, stress, physical activity, sleep, phone usage, Bluetooth [4], Distance, location, still duration, sleep duration, sleep dept, phone usage, desk sessions [35] |
| Promotion              | Physical activity, HR, stress, phone usage, Bluetooth, sleep, distance [37] |
| Cognitive load/interruptibility | HR, HRV, EDA, skin temperature, wrist movements [38], Speech, computer activity, calendar [30], HR, HRV, step count, sleep, circadian rhythm [39], Computer activity [22] |
| Misc. workplace activity| EDA, blood volume pulse (BVP), acceleration, phone usage [40], Computer activity [28], [30], Speech, calendar [30], User activity, application usage, location, ringer mode [41], Bluetooth [42], Computer-assisted protected time [43], [44] |

(ST). The study uses Salivary cortisol as the ground truth to assess the baseline stress levels of the workers, obtaining an accuracy of about 73% when distinguishing between low, medium and high stress level of the workers. Similarly, Mark et al. [29] discovered in their research on information workers that there was a direct correlation between the daily time spent on emails (captured via activity logging software) and increased levels of reported stress. In a bid to craft a stress-reduction intervention for the workplace, Howe et al. [12] conducted a four-week longitudinal study involving 86 participants to explore how the type and timing of interventions influence their usage, effectiveness in reducing stress, and user preferences. The authors utilized various signals including email, calendar entries, time of day, facial images, and heart rate data in their analysis. The authors conclude that digital micro-interventions successfully alleviate short-term stress in the workplace, advocating for their immediate incorporation into work settings to yield positive effects.

Another health-related issue that is of frequent interest is sleep. In one study of 138 individuals working as full-time nursing professionals, Feng et al. [19] use PPG based HR from Fitbit, sleep duration, sleep efficiency, REM Sleep duration features to gauge sleep quality of the participants. The study uses the Pittsburgh Sleep Quality Index (PSQI) [47] survey responses from participants as the ground truth. A score above 7 is taken as one class (potential sleep disorders) and a lower score is associated with the remaining class. The authors propose an optimization problem to identify the key meaningful motifs. Motif features obtained using the proposed pipeline results in higher performance while predicting sleep quality – while Fitbit summary results in 61.90% F1 score, the motif extracted from the proposed pipeline results in 77.47% F1 score. As wearable-based sleep detection is increasingly being used and relied on, one research work investigates its accuracy while tracking 700 information workers throughout a year using wearables and phones [20]. Martinez et al. report that wearables can overestimate sleep and they propose fusing phone usage activity (i.e., whether the phone is being used) with wearable data to mitigate this. Using the proposed approach, authors generate better models of self-reported sleep for the information workers than using either stream alone.

Worker’s affect, emotions and mood have also been studied in this domain. For example, Bin Morshed et al. [21] explore mood instability of 603 information workers and find that the
sleep and activity duration obtained from a Garmin wearable are negatively correlated with mood instability scores. The authors compute mood instability in the study using self-reported positive and negative affect schedule (PANAS) [48]. Umematsu et al. [13] use wrist wearables that capture skin conductance, skin temperature and acceleration from 39 workers in a Japanese company over a 30-day period. Stress, mood and health scores are collected every morning, using self-reported scores from 0 to 100. The authors then try forecasting the scores for the next day using the previous day’s physiological data. They obtain a mean absolute error of 13.47, 14.09 and 18.51 while predicting stress, mood and health score respectively. For fine-grained mood classification, Zenonos et al. [26] proposed a framework that classifies eight different types of moods into five categories using sensor data such as heart rate, pulse rate, PPG, ECG, skin temperature, etc. Mark et al. [23] studied how workers’ moods were connected to the amount of time they spent on emails. They found that email usage had a negative correlation with mood balance: the more time someone spent on emails, the worse their mood became in comparison to their positive feelings.

In another study of 50 hospital workers which also uses PANAS, Nadarajan et al. [23] find that speech activity can explain some variance in predicting positive affect measure. Employees wear a specifically designed audio badge during their work-shift hours. The authors extract several features from the audio to identify foreground speech. They then use a linear mixed effects model to estimate positive and negative affect from foreground activation (i.e., the percentage of recording time that foreground speech is present). Similarly, in another study, Robles-Granda et al. [16] utilize multiple sensing modalities to assess anxiety, sleep and affect of 757 information workers. Sensing modalities include wearable, phone application, Bluetooth beacons and social media. Models trained on the fusion of all the features from different sensing modalities leads to up to 13.9% improvement in the symmetric mean absolute percentage error (SMAPE) when predicting affect, anxiety and sleep quality scores.

In yet another study, Booth et al. employ multiple sensing modalities to study stress, anxiety and affect of hospital workers [18]. The ground truth for stress and anxiety are obtained as self-reports on a 5-point Likert scale, whereas PANAS is used for assessing affect. The work investigates how patterns in movement data in the workplace can relate with mental wellness. The hospital staffs carry a Bluetooth tag with them which communicates with several Bluetooth hubs placed in different rooms of the hospital. The nearest hub which has the highest RSSI is taken as the location estimate. For each consecutive data in which the participant is in the same location, authors record the entry time, the location and the duration spent there. The authors extract motifs from each time series of locations where participants linger and cluster these motifs to capture temporal relationships between rooms. Authors obtain 58% accuracy while classifying the mental wellness of the participants (between a binary label with one value representing high stress, negative affect, and anxiety, and the other value representing low stress and positive affect) using the combination of extracted motif features with Fitbit data (step count, heart rate and sleep) and smart shirt data (heart rate, breathing, acceleration etc.).

Other health and wellbeing related topics that have been studied using passive sensing among workers include focus and awareness. Soto et al. utilize biometric data from an arm-wear (viz., physical activity, HR, skin response, skin temperature and respiration) to estimate worker’s stress, focus and awareness [25]. The study ran for 8 weeks with 14 knowledge workers working at a large power and automation company. The ground truth for awareness and focus along with stress were obtained as self reports from the participants. The authors report that personalized models outperformed generic model, predicting baselines ranging from 3% improvement to up to 52% improvement in the precision, recall and accuracy score. There are also several other works that fuse passive sensing data with some other modality to assess wellbeing. For instance, Saha and Grover et al. [49] propose contextualizing on offline behaviors as obtained from passive sensors to make models better adapted to the social media signals. Authors first cluster participants based on the passive sensing data obtained from their wearable, Bluetooth beacons and smartphone application. Thereafter, they use social media derived features to predict different constructs within each cluster, obtaining an improvement on the baseline generic model by up to 5.43% in predicting self-reported anxiety, affect and sleep quality of information workers.

Passive sensing technologies are also being embraced by organizations to promote employees’ wellbeing. Organizations make use of gamification, personalized recommendations or even offer incentive programs to encourage employees to be more active in their day-to-day life [8]. Researchers studying the use of wearable technologies in corporate wellness programs report that their usage has a positive impact on employee wellbeing and health [50]. Passive sensing technologies, thus, can not only be used to monitor and assess health and wellbeing of workers, but they may also be utilized for health interventions and promoting a healthy lifestyle for the workers.

B. PRODUCTIVITY

Driven by the early success in the assessment of wellbeing in organizations, researchers have turned their focus to the use of passive sensing in the assessment of workplace performance. By tracking behaviors, recent work has attempted to characterize workplace performance with the long-term goals of identifying the behaviors that support productivity as well as generating interventions that might improve it. Nevertheless, quantifying workplace performance in an objective yet generalizable manner remains a challenge in the area. For instance, Amazon uses passive sensing on smartphones to measure the performance of their drivers and make sure that they avoid potentially dangerous behaviors like checking the phone while driving. However, phone usage could be the desired behavior in a different job, e.g., consulting.
Therefore, researchers in the pervasive computing community have often turned to job performance inventories developed by psychologists as ground truth to measure perceived workplace performance across organizations and industries in a generalizable manner. They have used passive sensing to predict participant scores for these inventories, or to classify individuals into higher and lower performers within the workplace. The inventories usually measure either task performance such as Individual Task Proficiency (ITP), In-Role Behavior (IRB); or assess behaviors that promote the effectiveness of organizations and its members such as Interpersonal and Organizational Deviance (IOD-ID, IOD-OD), Organizational Citizenship Behavior (OCB).

Task performance refers to duties or actions that are formally recognized and rewarded by management [51]. Several studies attempt to predict ITP and IRB as measures of task performance. In a study of 84 full-time nursing professionals over a ten-week period, Feng et al. [32] use Fitbit and Bluetooth proximity data to study how an individual’s physiological responses vary according to the work environment (room and function of the room). The authors compute a measure of mutual dependency of time in each room in the hospital and physiological responses and find this measure along with baseline aggregated features (e.g., min, mean, max, SD, etc.) leads to predictions of ITP with an adjusted R2 score of .11 and .12 for IRB. Another study [34] recruits 67 nurses and instruments them with a sociometric badge capable of measuring physical activity, speech activity, face to face interaction and social network inferred through the sociometric badge proximity sensor. Multiple linear regression models with sensed features as predictors are able to predict 49% of the variance in groups’ perception of workload as measured in an ad-hoc survey and 63% of the variance in groups’ perception of productivity.

In studies of information workers, several works stand out. The study by Das Swain et al. [33] recruits 249 individuals over 62 days and used Bluetooth beacons to analyze desk and away-from-desk sessions per hour, time at work and time at home. The authors produce a measure of organization fit by analyzing the convergence of individual routines in the aforementioned behaviors and their organization’s normative behavior. They find that a linear model with Big Five Personality [52] measures along with routine fit could predict up to 28% of the variance in IRB, with routine fit having a significant ($p < 0.05$) positive association with IRB. In another study of 603 information workers over 110 days, Das Swain et al. [35] propose the concept of organizational personas, a clustering-based approach in which personality facets are constructed over Big Five Personality data and activity facets are constructed from multi-modal data from a fitness tracker, a phone agent (location, phone usage) and Bluetooth beacons (desk sessions). The authors report that the activity facets account for a small but statistically significant part of the variance in ITP. In a similar study of 554 information workers using a phone agent, beacons and a Garmin fitness tracker, Mirjafari et al. [4] use K-Means clustering on the participant averages of ITP, IRB, OCB, IOD-ID and IOD-OD scores to classify them into higher and lower performers in their organizations. Results indicate that features from the fitness tracker alone can discriminate performers with an AUROC of .72; features from the phone agent can discriminate performers with an AUROC of .65 and features from both can do so with an AUROC of .83; showing how multi-modality can better explain these complex behaviors.

In a follow-up study of 298 information workers, Mirjafari et al. [53] used auto-encoder-generated features based on passive sensing data from mobile phones and a Garmin fitness tracker to predict day-to-day job performance dynamics, i.e., detecting whether there was an improvement, decline, or no change in the job performance for individuals in the study as assessed by ITP, IRB, OCB, IOD-ID and IOD-OD. The final model used XGBoost to achieve an F1 score of 75%, surpassing the authors’ baseline of 33%. The authors also show the use of Gradient Analysis, a technique popular in the computer vision domain [54], [55], to provide user-actionable interpretation of the model, demonstrating the potential to inform individuals of what behaviors should be modified in order to improve their performance. Similarly, Mark et al. [29] captured time spent on email interactions of 40 information workers using an activity logging software finding that the more time people spent on emails daily, the lower their reported levels of productivity is.

In the behavioral side of workplace performance inventories, IOD-ID and IOD-OD are measures of “bad” conduct in the workplace. Behaviors that indicate IOD-ID can involve cursing a co-worker, playing pranks, or making fun of someone. Behaviors that indicate IOD-OD can be tardiness or absenteeism, leaving work early without permission, putting little effort into work, among others [56]. On the other hand, OCB is a measure of “good” behavior. OCB is composed of behaviors that reflect altruism, conscientiousness, sportsmanship, courtesy and civic virtue [57]. Several studies have focused on these measures.

Feng and Narayanan [10] propose a method for capturing behavioral consistency in wearable data using the activity curve model. They find that consistency features improve accuracy by up to 6% when compared to using only summary features from the Fitbit fitness tracker in a study of 97 hospital workers throughout 10 weeks. Nepal et al. [56] use commute based passive sensing data (viz. location-related context, physiology, variability) from phones and wearables to predict the OCB and IOD score of workers. Authors collect passive data of 275 workers throughout a year while the workers are commuting to and from work. They train a stacked machine learning model on the commute data and achieve MAEs of less than 10% of each performance ground truths, suggesting that passive sensors may be capable of measuring an individual’s commuting experience and its impact on their job performance. In a previously mentioned study by Feng et al. [32], the mutual dependency between physiological response and time spent in different environments at the workplace improves the prediction of IOD-ID (adjusted R2 = 0.065) and IOD-OD (adjusted R2 = 0.092) as well. Mirjafari
et al. [4] find in their classification of higher and lower performers that passive sensing data is associated with IOD-ID, IOD-OD and OCB. Das Swain et al. [35] also report that the activity facet created from passively sensed data is associated with IOD-OD, IOD-ID and OCB. They also find that a better fit between individual and organizational desk routines measured through beacon proximity implied lower IOD [33]. However, maximum accuracy was still low with 62.4% for IOD-ID, 60.6% for IOD-OD, 56.6% for OCB, and 57.8% for STAI.

The work by Nepal et al. [37] follows a different line of research. Instead of attempting to predict subjective performance measures from objective data, it intends to find what objective data is related to individual success in organizations, i.e., getting promoted. The authors note that if promotion can be detected and it produces objective physiological signals, researchers could learn from these signals and through the study of job promotion – which could be inferred – what behaviors could be behind the high performance that granted the promotion to measure them objectively, foster them and replicate them.

In the modern era, nurturing collaboration through open offices has become the norm and workers face necessary interruptions throughout their workday to efficiently tackle problems. However, there are studies demonstrating that the nature and timing of interruptions negatively affect workplace productivity [58], [59] and increase worker stress [60]. Therefore, evaluating interruptibility has significant value to companies in terms of cost and time. To continuously measure a person’s interruptibility, Zuger et al. [39] study 13 software engineers over two weeks using wearable sensors in addition to keyboard and mouse interaction data. The ground truth in this study was collected using a pop-up question during work which asked the user to rate their interruptibility on a 1—7 Likert scale, and these ratings are further grouped into three states (12—345—67) for classification. Ultimately, they predicted interruptibility accurately (68.3%) by training a random forest on several features extracted from sensor modalities like heart rate, activity, and sleep.

Other works target efforts to support the design of future interventions in the workplace. Kimani et al. [30] created a conversational agent designed to assist information workers in achieving various work-related objectives, such as task scheduling and prioritization, task switching, providing reminders to take breaks, minimizing social media distractions, and reflecting on completed tasks. This agent also harnessed contextual data about the user to determine the optimal times for proactive intervention. Implemented among 24 information workers for a duration of six days, the agent analyzed speech, facial imagery, and computer usage patterns. The findings indicated that many participants not only appreciated the agent’s recommendations regarding breaks and work reflections but also became more conscious of their work habits. This heightened awareness led some to alter their routines for enhanced productivity and wellbeing. Nepal et al. [31] develop a Large Language Model (LLM) powered personalized productivity agent that utilizes computer-based telemetry data from information workers to provide tailored assistance. Authors highlight the importance of user-centric design, adaptability, and the balance between personalization and privacy in AI-assisted productivity tools. Similarly, Kadoya et al. [61] use a wearable to derive control measures to understand the relation of emotional states and productivity in the workplace. Such understanding would help in the future to focus interventions that can improve the emotional state of workers. Mark et al. [22] found that affect balance correlates with concentration and workplace productivity, and sleep measured by a fitness tracker was related to affect balance. In another study, Schaul et al. [38] designed a proof of concept system that integrated a smartwatch to predict office workers’ cognitive load and suggest when users were available to be interrupted. Similarly, Di Lascio et al. [40] show that wearables can predict workplace activity passively, which has the potential to be used as the foundation of systems to automatically block distractions during focus hours and to suggest breaks. Kucukoz-Cavdar et al. [41] also create a model for predicting office workers’ availability and inclination to take breaks using mobile sensing features relevant to workers’ location, activity, application usage, ringer mode. Das Swain et al. [43] evaluated the effect of computer-assisted protected (CAP) time on 89 information workers. Through a randomized control trial in naturalistic conditions, they found that CAP significantly benefits workers who have never used such automated schedulers. Similarly, Saha et al. [44] found that CAP improved positive well-being factors such as relaxation while reducing negative aspects like anger. To summarize, these studies not only advance our understanding of workplace performance and the behaviors that bolster productivity but also showcase the pervasive computing community’s active efforts in crafting interventions that enhance performance. With the rapid advancement and integration of LLMs and artificial intelligence (AI), this field stands on the brink of a significant growth trajectory. The combination of passive sensing with the nuanced analytical capabilities of LLMs presents an exciting next frontier, promising to redefine and amplify intervention strategies for workplace productivity and wellbeing.

V. DISCUSSION

The works discussed in this article follow a wide variety of approaches to solve the problem of assessing wellbeing and productivity through passive sensing in-situ. In what follows, we discuss some considerations to take into account for Future of Work research.

A. Considerations for Ground Truth

While adapting to the Future of Work, researchers need to make additional considerations beyond simply selecting validated survey instruments. For instance, surveys at the workplace could bias participants from being candid because of employer surveillance. However, remote work might mitigate such concerns. Alternatively, many wellbeing constructs can be measured through physiology (e.g., cortisol), but when
the workforce is distributed across diverse work spaces, such measures could include unforeseen artifacts which a consistent workplace would otherwise insulate. Similarly, for productivity measures, while task performance is important, for certain job roles deviance measures or citizenship behavior could provide a more appropriate view of performance. Apart from careful selection of ground truth instruments, researchers should collaborate with industrial and organizational psychologists and personnel management teams to learn which forms of estimations are most relevant to them — whether that be categorical classifications or continuous evaluations.

B. Considerations for Sensor Deployment

Ideally, the set of constructs that researchers want to investigate drives the choice of sensors. However, especially while estimating new measures, it can be challenging to ascertain a finite combination of sensors to deploy. Moreover, deployments are expensive and challenging. In longitudinal in-situ studies, even if issues like privacy concerns and maintenance of the sensing infrastructure can be mitigated, lack of participant compliance can deteriorate the quality of data. Also, it may not be practical for all researchers to install a large suite of sensors and triage which signals are actually meaningful. In such cases, researchers can consider forms of low-burden sensing such as logging social media behavior. Therefore, we need to select sensors that sustain minimum burden on the user and still provide data consistently. Furthermore, the deployment of passive sensing technologies, as explored in a case study on just-in-time emotional support agents, underscores the importance of addressing boundary misalignments, data ownership, and power dynamics to facilitate successful implementation. These considerations highlight the nuanced challenges of deploying personalized sensing systems in both work and nonwork contexts, emphasizing the need for careful alignment with user values and wellbeing definitions.

C. Considerations for Machine Learning Models

The workplace is a dynamic context and therefore passive sensing studies tend to be in-situ studies over large periods of time. This approach comes with the caveat of missing data that can make it challenging to train models, especially when considering sensors that require constant skin contact that can be affected by movement or simply forgetfulness, as is the case with wearable devices. In addition, missing data is often not missing completely at random, meaning that simply ignoring missing data as is done in several studies can lead to a biased sample. One way researchers can mitigate this for behavioral data is by exploiting complementary streams of data to impute the missing data. On the other hand, a large set of time-varying features opens an array of potential learning approaches, e.g., moment statistics, regularity, or auto-encoders. Researchers can empirically compare approaches to find the best model, but also consider other aspects like interpretability and transferability to select learning approaches.

D. Privacy and Ethical Considerations

While we primarily highlighted the opportunities and potentials of these technologies and methodologies, these also come at a cost. For example, despite the best intentions, when instrumented at workplaces, these approaches can bear ethical and privacy concerns. There are lingering questions regarding the best practices of these algorithmic inferences for real-world measures and high-risk decisions because these approaches can be misused in ethically questionable ways. Consequently, these approaches and technologies can compromise privacy, defy expectations, and damage the trust between individuals and technologies. Park et al. identified key themes that negatively affect employee perception of AI use in the workplace, and suggest increased transparency and human-in-the-loop interventions as solutions. Table I shows that several approaches rely on sensing that occurs most often outside the workplace, e.g., sleep and physical activity, sensing for which there is no conceivable way to acquire consent from all involved parties such as speech activity, or sensing that could be carried out using the sensors in devices that could be provided by employers or fall into Bring-Your-Own-Device (BYOD) policies such as mobile phones. In fact, consenting to a passive sensing study in the workplace is complex because of the associated power dynamics. A study by Chowdhary et al. reveals that the passive sensing framework must support meaningful consent that is freely given, reversible, informed, enthusiastic, and specific.

In fact, employer surveillance and employee’s subjective expectation of privacy share a competing relationship and only a thin line of difference exists in perceiving the same technology as for surveillance or for supportive intervention. There is a need to ensure that future work applications benefit individuals without sacrificing their privacy or forcing them to adopt behaviors solely on the need for increasing productivity in the workplace according to arbitrary metrics. A recent study by Das Swain et al. interviewed 28 information workers about passive sensing in the workplace. Some concerns the workers talked about include the need for distinction between work and personal life, re-appraising sensor data through human evaluation, the dehumanizing nature of quantifying performance continuously, and selective sharing of data. This calls for the need to design guidelines that lead to responsible applications that balance the trade-offs of the risks and benefits associated with these data-driven human-centered assessments. In addition, these guidelines should prevent the ingraining of biases in automated decisions and performance-evaluation systems, a danger made obvious by early attempts at developing AI tools for recruiting that resulted in biased results. Considering the lack of diversity in the tech industry in the US, there is a considerable risk that the training of models based on existing employee data without special consideration of disproportionate representation could result in AI-based tools encoding biased behaviors that are not truly supporting task performance improvements for the companies or well-being...
benefits for the employees. These aspects should not be taken lightly and researchers should also incorporate metrics of AI fairness [83] and potential harms [71] when conducting future work studies that predict performance outcomes.

E. Limitations and Future Work

The existing body of work highlights several challenges with data-driven human-centered assessments to facilitate workplace outcomes. Many of these challenges suggest interesting future directions. In terms of operationalization, there is a lack of availability as well as a consensus about the definition of “ground-truth”. While self-reported measures are considered to be the gold-standard source of data, self-reported data bear their own limitations and biases. Moreover, from a methodological point of view, most of the approaches are not generalizable across problem scenarios or datasets — the same approach may not work on different populations or a different outcome measure. This necessitates accounting for domain information and problem-centric adjustments for model tuning.

Again, this field is evolving and most of the extant research is formative in revealing the feasibility and efficacy of these technologies. However, real-world and prospective adaptations of these approaches may bring in new challenges. For instance, the accuracy metrics tend to reflect the model performance at average, however, false positive on single instances (a single individual) may bear larger risks related to hiring or firing employees. This motivates thinking about novel measurement approaches that weigh in the risks and qualitative assessments beyond quantitative accuracy measures. These models not only need to be rigorously tested, but also proper guidelines need to be set about the role of algorithmic inference and human judgment. All in all, this literature survey shows us the potentials of passive and ubiquitous sensing methodologies within the context of Future of Work. However, there are several issues such as scalability, generalizability, privacy and ethical concerns which hinder the broad adoption of such technologies in spite of the widespread enthusiasm. Therefore, much work is needed to make workplace sensing ubiquitous. It is also important to highlight that our survey specifically focuses on recent advancements in the field, prioritizing works published since 2015. This criterion, among others, influenced the selection of studies, leading to the exclusion of older yet potentially relevant research. To ensure transparency and provide a broad perspective, we recommend readers refer to additional surveys that encompass the wider scope of developments in this area [84]–[88].

VI. CONCLUSION

In this survey, we have showcased the latest and most pertinent studies that illuminate current research trends and the promising future of passive sensing technology in the workplace. Much of the research we have discussed is still unfolding, with data-driven investigations paving the way for identifying the most effective sensor streams and models to encapsulate various aspects of the workplace and its workforce. We have also pointed out several unresolved issues and viable pathways for the integration of passive sensing into the Future of Work landscape. As this field is just beginning to bloom, it is intriguig to consider how the integration of advancements in AI and LLMs with passive sensing research could potentially pave the way for innovative developments. While examples within our survey are yet to explicitly showcase this fusion, it is reasonable to anticipate that such advancements may offer promising directions for enhancing workplace productivity and wellbeing in the future.

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