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Original Article

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Derivation of Time-Activity Data Using Wearable Cameras and Measures of Personal Inhalation Exposure among Workers at an Informal Electronic-Waste Recovery Site in Ghana

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Abstract

Objectives: Approximately 2 billion workers globally are employed in informal settings, which are characterized by substantial risk from hazardous exposures and varying job tasks and schedules. Existing methods for identifying occupational hazards must be adapted for unregulated and challenging work environments. We designed and applied a method for objectively deriving time-activity patterns from wearable camera data and matched images with continuous measurements of personal inhalation exposure to size-specific particulate matter (PM) among workers at an informal electronic-waste (e-waste) recovery site.

Methods: One hundred and forty-two workers at the Agbogbloshie e-waste site in Accra, Ghana, wore sampling backpacks equipped with wearable cameras and real-time particle monitors during a total of 171 shifts. Self-reported recall of time-activity (30-min resolution) was collected during the end of shift interviews. Images ($N = 35{,}588$) and simultaneously measured $PM_{2.5}$ were collected each minute and processed to identify activities established through worker interviews, observation, and existing literature. Descriptive statistics were generated for activity types, frequencies, and associated $PM_{2.5}$ exposures. A kappa statistic measured agreement between self-reported and image-based time-activity data.

Results: Based on image-based time-activity patterns, workers primarily dismantled, sorted/loaded, burned, and transported e-waste materials for metal recovery with high variability in activity duration. Image-based and self-reported time-activity data had poor agreement (kappa = 0.17). Most measured exposures (90%) exceeded the World Health Organization (WHO) 24-h ambient $PM_{2.5}$ target of 25 µg m^{-3}. The average on-site $PM_{2.5}$ was 81 µg m^{-3} (SD: 94). $PM_{2.5}$ levels were highest during burning, sorting/loading and dismantling (203, 89, 83 µg m^{-3}, respectively). $PM_{2.5}$ exposure during long periods of non-work-related activities also exceeded the WHO standard in 88% of measured data.

Conclusions: In complex, informal work environments, wearable cameras can improve occupational exposure assessments and, in conjunction with monitoring equipment, identify activities associated with high exposures to workplace hazards by providing high-resolution time-activity data.

Keywords: developing countries; electronic-waste; time activity; informal sector; job exposure matrix; particulate matter; personal inhalation exposure; wearable camera

Introduction

Improved methods for occupational exposure assessment can contribute to health and well-being among the world's estimated two billion informally employed workers (International Labour Office, 2018). These workers are not subject to national labour standards and are at substantial risk of hazardous work conditions, including high levels of exposures to toxic agents with little or no social, economic, or occupational protections (Chen, 2012; International Labour Office, 2018). The unregulated and unorganized structure of informal worksites limits data collection, establishment of linkages with adverse health effects, and design and implementation of risk-mitigating strategies.

Combining task-specific time-activity measures with task-specific exposure concentrations enhances the ability to estimate levels of personal occupational exposure. Task-specific exposure estimates help establish exposure groups and dose–response relationships between exposures and measured health outcomes (Checkoway *et al*., 2004). Additionally, time-activity can reveal risk factors that may affect an employee's health. In informal sectors, collection of time-use data using standard methodologies, such as written diaries, may lack the precision to detect acute exposures.

In the informal electronic-waste (e-waste) recovery sector, hazardous work conditions and environmental pollution have raised considerable alarm (Heacock *et al*., 2016). Up- and downstream solutions are urgently needed to redesign the organizational structures that handle global e-waste (Bakhiyi *et al*., 2018). Task-specific exposure information is needed to identify high-risk worker groups, strengthen causal evidence of adverse health outcomes, and motivate stakeholder action and interventions.

At the Agbogbloshie informal e-waste recovery and scrapyard in Accra, Ghana, job titles, schedules, and task protocols are unavailable, so previous studies derived exposure groups using alternate methods. Interviews revealed that most workers participated in an average of seven (maximum of nine) different jobs (Srigboh *et al*., 2016). Workers who sorted e-waste had blood-lead 2.2 times higher than non-sorting controls, and workers who burned e-waste had urinary copper and zinc 1.7 times higher than non-burning controls (Srigboh *et al*., 2016). No significant differences were found in elemental exposures when comparing workers across the primary job of the past 6 months (Srigboh *et al*., 2016). A study on noise exposure and heart rate used 15-min time-activity diaries and found that activity did not significantly confound or modify the observed positive association between noise and heart rate (Burns *et al*., 2016). The lack of detectable differences in exposure across self-reported primary job task or time-activity recall in these and other studies (Feldt *et al*., 2014; Wittsiepe *et al*., 2015) may be due to substantial task misclassification, which may obscure critical differences in associated health risks.

Airborne pollutants, such as particulate matter of aerodynamic diameter of ≤10 or <2.5 µm, PM_{10} and $PM_{2.5}$, are generated during e-waste recovery practices (Daum *et al*., 2017). The health effects associated with PM_{10} and $PM_{2.5}$ exposure (Brook *et al*., 2010; Anderson *et al*., 2012) may be modified by the types of tasks workers perform. There are no published comprehensive evaluations of general or task-specific personal inhalation exposure among informal e-waste workers. One small-scale study (n = 5) sampled the breathing zone of informal e-waste recovery workers at Agbogbloshie and found levels of aluminium, copper, lead, iron, and zinc that exceeded workplace limits (Caravanos *et al*., 2011). Comprehensive data could guide risk-mitigating interventions and enhance our understanding of how elevated chronic and short-term peak exposures to PM typical of other informal sector settings affect health (Smith and Peel, 2010).

This study aims to address the gaps in exposure assessment in informal settings by using wearable cameras and personal exposure monitoring equipment to generate task-specific exposures. We utilize an ongoing longitudinal cohort study based at the Agbogbloshie e-waste recovery site, the West Africa-Michigan CHARTER II for GEOHealth (GeoHealth-II), designed to assess environmental and occupational health hazards and overcome limitations of prior studies. Data for this study were collected among e-waste worker participants (N = 142) between March 2017 and April 2018. Self-reported and image-based time-activity data are used to characterize the type and duration of tasks performed by e-waste workers on the Agbogbloshie informal site. The agreement between sources of time-activity data is quantified. Image-based time-activity is used to identify activities strongly associated with high concentrations of contemporaneously measured personal $PM_{2.5}$, i.e., burning and dismantling e-waste. The method described in this article for using wearable cameras to derive validated and time-resolved time-activity data can be adapted for occupational settings with an urgent need to identify sources of acute exposures and other hazards.

Methods

Study location and worker population

The Agbogbloshie e-waste and metal scrapyard in Ghana is a 0.5 km^2 area near Accra's central business district and adjacent to a food market, industrial sector, and informal community with a population of 79 684 (2009) (Housing the Masses, 2009; Oteng-Ababio, 2012). Figure 1 provides an aerial view of Agbogbloshie. Prevailing winds are south, south-westerly. Workstations are not formalized and work- and non-work-related activities are adjoined; mosques, domiciles, food vendors, cattle, and other subsistence activities are interspersed among individuals or groups performing e-waste recovery tasks.

The site is overseen by the Scrap Dealers Association (SDA). Its chair reported not knowing the number of

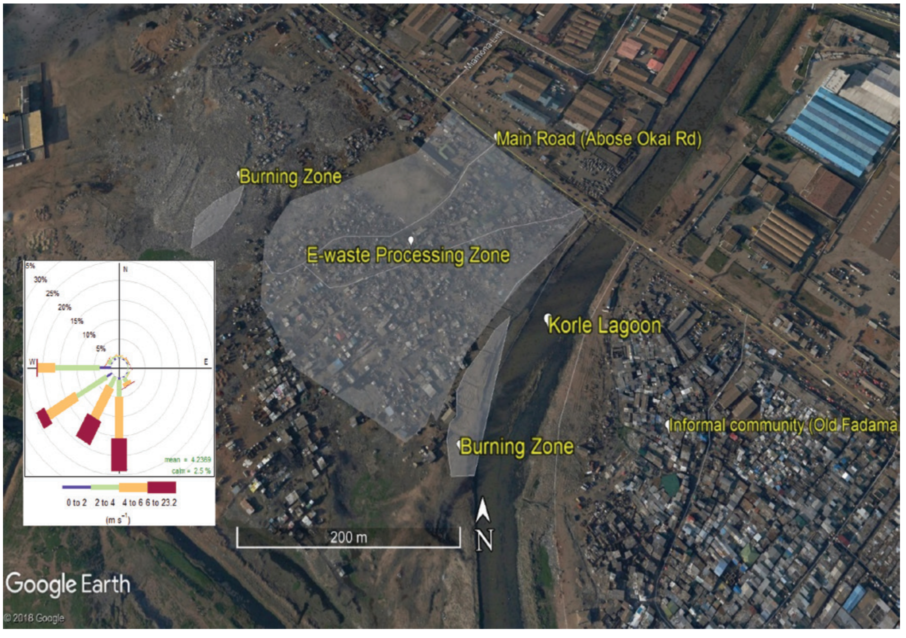

Figure 1. Agbogbloshie electronic-waste recovery site map. The Agbogbloshie site is located in Accra, Ghana. The yellow line indicates the main road, Abose Okai Road, adjacent to the site. The highlighted polygon labelled E-Waste Processing Zone is where dismantling, sorting, weighing, and some trading of e-waste occur. The highlighted polygons labelled Burning Zone indicates where e-waste is burned in open, surface fires. The larger and oldest burning zone is adjacent to the Korle Lagoon. The prevailing winds are south, south-westerly. Map created using Google Earth Pro V 7.3.2.5776. (10 July 2015). © Google 2018. Wind rose created using Integrated Surface Data collected at the Kotoka International Airport in Accra, Ghana. Data provided by the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (https://www.ncdc.noaa.gov/isd) (accessed on 9 January 2018).

workers on-site or if a new worker arrived in the preceding month. There are also no formal job titles or task protocols. The majority of workers who migrate to Accra from Ghana's rural Northern region seeking employment opportunities are in their 20s (Amoyaw-Osei and Agyekum, 2011). They are predominantly Muslim and Dagbani-speaking, thus differing from the Twi-speaking, Christian majority in Accra (Amoyaw-Osei and Agyekum, 2011).

Study sample

Participant data come from the GeoHealth-II longitudinal cohort study. Data were collected during three study waves (beginning in March 2017, August 2017, and January 2018) among e-waste worker participants (N = 142).

Following a public presentation on the study, workers who were willing to join the study were enrolled (n = 100). More workers requested enrolment than the study had resources for. Although recruitment was planned for wave I only, new participants were enrolled at wave II (n = 42), to replace those that were lost to follow-up between waves I and II. Follow-up visits occurred during waves II and/or III; participants were located by cell phone and with the help of seasoned workers. Of the 142 recruits, 70 completed all three waves, 35 completed two waves, and 37 completed one wave.

Informed consent was obtained, and questionnaires were administered by trained, local interpreters in the participants' native or preferred language: Dagbani, Hausa, Twi, or English. Participants were compensated at each wave with 30 Ghana Cedis (approximately US$7, roughly an average day's wage), a T-shirt, and lunch. The University of Ghana and University of Michigan Institutional Review Boards (IRB) approved the study protocols. The local chief of Agbogbloshie, and chair and vice-chair of the SDA gave permission and allowed the research team to enter the community.

Data collection

A diagram depicting the stages of data collection is available in Supplementary Fig. S1, available at *Annals of Occupational Hygiene* online. Wave I, II, and III were aligned with the dry, rainy, and Harmattan (winds coming off the desert) seasons, respectively, to achieve seasonal variation in work patterns and personal exposure.

Survey instruments

A questionnaire administered during baseline visits included an extended section on occupational history and job tasks. In wave II only, a time-activity diary with a 30-min resolution was administered by an interpreter at the end of personal monitoring sessions (see Supplementary Fig. S2, available at *Annals of Occupational Hygiene* online). Participants were asked to recall their activities from the time they started work. The diary included nine pre-selected e-waste recovery tasks identified in a prior study among Agbogbloshie e-waste workers (Srigboh *et al.*, 2016).

Wearable camera and personal PM monitoring

Three sampling backpacks containing a wearable, time-lapse camera and personal PM inhalation exposure equipment were deployed in the morning on all days excluding Sunday. Length of sampling was set to 4 h between 8:00 AM and 2:00 PM based on the observation that non-work activities increased in the latter half of the afternoon. Sampling duration was reduced to 2 h during wave III because of high levels of PM from Harmattan winds. Time-lapse images were collected in 1-min interval using a wide-angle GoPro Hero4© camera mounted to the backpack's forward facing shoulder strap. Minute-by-minute PM was measured using a five-channel optical particle counter (Aerocet 831, Met One Instruments, Inc., Grants Pass, OR), which converts counts into size-specific mass measurements (microgram cubic meter) using a proprietary algorithm. The instrument's concentration range is 0 to 1000 µg m^{-3}, beyond which particle coincidence error leads to under-reporting.

Deriving time-activity patterns from images

Two trained reviewers at the University of Michigan categorized images into activities using a data collection instrument designed on the Research Electronic Data Capture (REDCap) secure web platform (for a transcript of the instrument, see Supplementary Fig. S3, available at *Annals of Occupational Hygiene* online). Reviewer identified activities could come from a single image (e.g. smoking) or a group of images depicting one sustained activity. A checklist of objects helped characterize activities (e.g. flames indicated burning). This input and the response to subsequent questions about the specific activity that automatically followed were used to create time-activity patterns (TAP) for each participant.

TAPs are continuous, detailed, and time-specific logs of all activities performed by a participant. Each TAP comprised a time-ordered series of 'events'; an event comprised one or more consecutive images that identified a sustained work- or non-work-related activity

Figure 2. Visual activity dictionary. The images used in this visual task dictionary were taken by wearable cameras worn by study participants during their work day as an e-waste recovery worker. The exemplar images demonstrate how time-activity data can be derived using time-lapse images.

(Fig. 2, available at *Annals of Occupational Hygiene* online). Because our focus was on detecting work-related activities, brief periods of rest and position changes (≤5 min) bounded by the same identifiable activity were not recorded as separate events.

TAPs from pilot data were discussed with workers during four on-site interviews to confirm the accuracy of activity classifications. Workers described the activities from a series of images depicting all work- and transportation-related activities, in addition to some images with unclear classifications. The interviews revealed a distinction in how workers and reviewers classified some activities. Workers identified a task from one sub-task; for example, what a reviewer described as 'bicycle transit', a worker named 'collecting'—the term used for travelling off-site (often by bicycle or tricycle) to purchase or scavenge e-waste materials. Reviewers unfamiliar with a worker's intent were instructed to classify sub-activities to detect specific activities associated with high levels of inhalation exposure. This learned information was taken into consideration when testing agreement with worker's self-report.

The final instrument's work-related categories included burning wires, burning material other than wires, starting or igniting a fire, stripping wires, dismantling/pounding/breaking, on-/off-loading, gathering/sorting, transporting materials (off- or on-site), trading/selling, weighing, repairing, and smelting (lead or aluminium) (for descriptions, see Supplementary Table S1, available at *Annals of Occupational Hygiene* online). Images, which showed that the sampling backpack (including the camera and PM monitoring device), was not being worn as intended were categorized as 'unusable'. Images of backpack deployment and retrieval were categorized as 'staging area'. For more details of image-processing steps and output, see Supplementary Table S2, available at *Annals of Occupational Hygiene* online.

Creating an averaged database of PM and TAP

The minute-by-minute TAP database was merged with contemporaneous minute-by-minute size-specific PM levels using participant ID, date, and time. Additionally, a 5-min average database was made to reduce sampling noise associated with PM measures and a 30-min averaged database was made to test agreement with self-reported time-activity diaries. For the averaged databases, the most frequently occurring activity within each 5- or 30-min period was selected to be representative (further coding details in Supplementary Table S2, available at *Annals of Occupational Hygiene* online). 'Unusable' images were removed post-averaging if they were the dominant event for the averaged interval.

Statistical analyses

The baseline questionnaire was used to describe job characteristics and task history. The image-based 1-min TAPs were used to describe the type and duration of all activities performed during waves I, II, and III. To measure the agreement between self-reported and image-based time-activity, a subset of wave II diaries and 30-min TAPs were used. Unweighted kappa statistics were calculated to measure agreement beyond chance. A kappa score was calculated for time-activity designation based on eight activity categories [burning, dismantling, material movement and organization, buy/sell/weigh, repairing, smelting, other (work-related), non-work] (for details on activity categories, see Supplementary Fig. S2, available at *Annals of Occupational Hygiene* online).

The 5-min TAPs were used to evaluate the capacity of image-based time-activity data to detect job tasks that were strongly predicted to have the highest concentrations of $PM_{2.5}$ inhalation exposure. Data collected during an urban fire near Agbogbloshie were excluded from the 5-min TAPs (n = 695 min) and PM summaries. Descriptive statistics of $PM_{2.5}$, PM_1 (aerodynamic diameter ≤ 1 µg), $PM_{10-2.5}$ (the coarse fraction of PM calculated using the difference method), and total suspended particulate (TSP) are summarized by activity. Exposure groups based on cut-off points derived from the 25th, 50th, 75th, and 95th percentiles of $PM_{2.5}$ were used to examine the amount of time participants spent in each exposure group by activity. The non-parametric Mann–Whitney U test compared $PM_{2.5}$ concentrations in our subsample with those of the excluded 'unusable' data in which participants removed their sampling backpacks. All analyses were accomplished using the statistical software R (R Core Team, 2016).

Results

Of the 142 baseline occupational questionnaires, one participant was excluded due to missing over 90% of responses, resulting in a final selection of 141 participants. Personal monitoring with images and PM levels was completed in 63 days between March 2017 and February 2018 (22, 20, and 21 days in waves I, II, and III, respectively) by 110 unique participants. Our final 1-min database comprised 32 439 classified images with contemporaneous PM estimates from 109 unique participants after excluding 'unusable' images (n = 3,149, which included all images from one participant) (see Supplementary Fig. S1, available at *Annals of Occupational Hygiene* online). A unique participant completed either one (n = 55), two (n = 47), or all three (n = 7) waves resulting in 170 partial-shift samples. The mean sampling durations per partial-shift were 210 (SD: 102), 211 (SD: 72), and 153 (SD: 80) min in waves I, II, and III, respectively, and close to the targeted sampling duration (240 min in waves I and II and 120 min in wave III).

Self-reported and image-based time-activity

Participants were an average of 27 years old, over 90% were Muslims originating from the Northern region of Ghana with mostly low education and income, and over 70% earned the equivalent of less than 10 USD per day (see Supplementary Table S3, available at *Annals of Occupational Hygiene* online). Eighty-eight percent of participants lived on or within 1 km of the e-waste site and worked 6–7 days a week for an average of 10 h per day. Participants reported working at Agbogbloshie for an average of 8.6 years.

Dismantling e-waste followed by trading/selling and burning e-waste are the most commonly reported job tasks ever and currently performed at Agbogbloshie within the sample (see Supplementary Table S4, available at *Annals of Occupational Hygiene* online). Fewer than 10% reported repairing e-waste, weighing or smelting lead batteries. 'Other' jobs included mechanic and taxi driver. Almost all participants who reported performing a job in the past were still currently performing the same job. On average each participant reported having *ever* performed 3.2 jobs (range: 1–6) and *currently* performing 2.9 (range: 1–6). Survey data indicated wide differences in the percent of workers 'currently' performing a job with those reporting that job as their primary job (e.g. 82 participants reported 'currently' performing burning and 26 indicated that it was their 'primary job over the past three months'). These conditions reinforce the need for a real-time and objective method to accurately document time-activity.

Image-based results on the frequency, type, and duration of activities are summarized in Table 1. Reviewers classified a total of 910 events. Each TAP included an average of 5.6 events (range: 1–16) per participant. Event duration varied by activity (for details on activity-specific durations, see Supplementary Table S5, available at *Annals of Occupational Hygiene* online). Activity types and durations remained approximately equivalent across waves I, II, and III; however, the overall number of work-related events decreased from wave I to wave III, and the number of 'unusable' images increased.

Among work-related activities, representing 28% of sampling time (n = 8,806 images), dismantling (50%), sorting and loading (17%), burning (14%), and transporting materials (10%) were most common (Table 1). No participants performed smelting. 'Non-work-related' activities in which participants did not appear to be actively working represented 53% (n = 17 072 images) of the total sampling time. An estimated 66% of non-work-related activities occurred on the e-waste site based on the presence of objects indicative of the site (e.g. e-waste materials, tools, fire); however, the proportion is most likely higher. For transportation, participants primarily walked short distances [mean (SD): 16 (11) min] on or near the e-waste site.

Agreement

The self-reported diaries (30-min resolution) and matched 30-min TAPs used to test agreement are summarized in Table 2. This subset of wave II data covered three hundred and forty-nine 30-min intervals from 51 participant diaries (mean: 205 min/diary). The agreement was low (0.17), indicating 'none to slight' agreement (Mchugh, 2012). Sensitivity analyses examined

Table 1. Activities performed by e-waste worker participants during 170 partial-shift samples and derived using wearable camera time-lapse images (n = 31 837 images)

Task category	No. of events[a]	Duration (min)	Total (min)
	N	Mean (SD)	*N* (%)
Work-related events	212	41.5 (48)	8806 (27.7)
Burning	26	47.7 (42)	1240 (3.9)
Dismantling	75	58.2 (63)	4362 (13.7)
Sorting and loading	43	34.5 (43)	1483 (4.7)
Buy, sell, weigh	16	18.6 (12)	297 (0.9)
Transporting materials	40	21.3 (21)	851 (2.7)
Repair	1	16.0 (NA)	16 (0.1)
Other	11	50.6 (30)	557 (1.7)
Non-work-related events	344	49.6 (52)	17 072 (53.6)
Sitting	260	56.4 (55)	14 670 (46.1)
Smoking while sitting	24	43.4 (47)	1041 (3.3)
Eating or drinking while sitting	44	23.5 (26)	1033 (3.2)
Other	16	20.5 (18)	328 (1.0)
Transportation-related events	354	16.8 (16)	5959 (18.7)
Walking	256	16.1 (11)	4126 (13.0)
Bicycling	28	20.5 (15)	575 (1.8)
Motorbike or car	70	18.0 (27)	1258 (4.0)
Total[b]	910	35.0 (43)	31 837 (100.0)

[a]An 'event' is defined as a consecutive series of images of variable length depicting one sustained activity; event duration can range from 1 to n minutes.
[b]Out of a grand total of 35 588 images, 31 837 images were used after excluding n = 3149 unusable images (321, 789, and 2039 images from waves I, II, and III, respectively) during which the sampling backpack was removed by the participant, and n = 602 images taken in the staging area where devices were turned on and off and participants completed registration.

Table 2. Activity breakdown from self-reported diaries (30-min resolution) and matched image-based time-activity patterns (30-min resolution) collected during wave II from a subset of e-waste worker participants (n = 51)

	Self-reported[a]			Image based[b]		
	No. of 30-min periods	Time (30-min periods)		No. of 30-min periods	Time (30-min periods)	
	N	Mean (SD)	Total (%)	*N*	Mean (SD)	Total (%)
Activities						
Burning	7	4.6 (2)	32 (9.2)	2	4. (3)	8 (2.3)
Dismantling	21	6.9 (4)	145 (41.5)	11	4.3 (3)	47 (13.5)
Sorting and loading[c]	5	8.0 (5)	40 (11.5)	10	2.8 (2)	28 (8.0)
Buy, sell, weigh	8	5.1 (3)	41 (11.7)	3	2.3 (1)	7 (2.0)
Repair	NA	NA	NA	1	2 (NA)	2 (0.6)
Transporting materials[c]	1	9.0 (NA)	9 (2.6)	7	1.3 (0)	9 (2.6)
Other (work)	2	1.5 (1)	3 (0.9)	3	2.7 (2)	8 (2.3)
Non-work or transport	22	3.6 (3)	79 (22.6)	25	9.6 (8)	240 (68.8)
Total	66	5.3 (4)	349 (100)	62	5.6 (6)	349 (100)

[a]Self-reported time-activity diaries (n = 51) from wave II matched with image-based time-activity data by subject ID and date time.
[b]Image-based time-activity patterns (n = 51) from wave II matched with self-reported time-activity data by subject ID and date time.
[c]Sorting, loading, and transporting materials were combined into 'Material movement and transport' prior to testing agreement between the two sources of data with a kappa statistic.

sources of misclassification and revealed that agreement did not differ depending on the number of activities performed during the shift, but agreement improved if we ignored the time during which activities occurred. Under this scenario, the percent agreement was highest for non-work (96% agreement) and dismantling activities (40%) and lowest for buy/sell/weigh (15%) and burning (33%). In addition, participants occasionally reported performing an activity even if they were sitting near to where the activity was being performed by others. This was determined by reviewing all images for time-intervals in which a participant self-reported burning and the reviewer did not (n = 6 30-min intervals). In 50% of the images (n = 90), the participant was sitting in a rest-area located in proximity (approximately 10 m) to the burning zone, but not actively burning e-waste. The remaining images showed no evidence of burning or being located near the burning zone.

Personal inhalation exposure to $PM_{2.5}$

$PM_{2.5}$ concentration estimates are summarized by activity type in Table 3 and Fig. 3. Data excluded due to 'unusable' images had significantly lower mean $PM_{2.5}$ concentrations than our final sample (73 versus 81 μg m^{-3}, Mann–Whitney P-value: <0.001) (discussed further in Discussion section). Overall, the $PM_{2.5}$ arithmetic and geometric mean concentrations were 81 (SD: 93) and 60 (SD: 2.1) μg m^{-3}, respectively. The mean $PM_{2.5}$ concentrations for activities believed to have been performed on-site (based on objects identified in the images) were significantly higher than those performed off-site (85 versus 72 μg m^{-3}, Mann–Whitney P-value: 0.014) despite the fact that most off-site activities included travel on major roadways. Work-related activities had the highest mean $PM_{2.5}$ concentrations (100 μg m^{-3}) when compared with transportation- and non-work-related activities. Burning activities had the highest $PM_{2.5}$ exposures of all activities (203 μg m^{-3}). The mean concentrations for sorting/loading and dismantling were approximately 56 and 60% lower than burning, but still higher than all other tasks. At the same time, median $PM_{2.5}$ concentrations between work- and non-work-related activities were largely similar; all individuals on the site, regardless of their activities, experienced poor air quality. Inhalation exposure reached the highest exposure group ($PM_{2.5}$ > 184 μg m^{-3}) during 27% of time spent burning, 7% of time spent dismantling and transporting materials, and 6% of time spent eating and drinking (see Supplementary Fig. S4, available at *Annals of Occupational Hygiene* online). Workers performing burning activities also spent close to the longest amount of time in the lowest exposure group ($PM_{2.5}$ < 38 μg m^{-3}). The activity-specific distribution of coarse particulate and TSP are similar to findings related to $PM_{2.5}$ (see Supplementary Table S6, available at *Annals of Occupational Hygiene* online). One notable difference was the increased exposure to coarse PM during the transport of e-waste materials and 'other' work activities. Distinctions across activities were less apparent for PM_1.

Table 3. Distribution of size-specific $PM_{2.5}$ (µg m^{-3}) by activity type (image based)

Activities[a]	No. of 5-min periods	PM2.5 (µg m^{-3})								
	N	Geometric mean (SD)	Arithmetic mean (SD)	Minimum	P5	P25	P50	P75	P95	Maximum
Work-related events	1755	66.7 (2.2)	100.2 (144.2)	8.8	22.7	39.9	62.1	96.7	325.9	1501.4
Burning	249	90.4 (3.3)	202.8 (300.9)	16.1	24.5	35.6	57.0	223.0	912.4	1501.4
Sorting and loading	301	67.6 (1.9)	82.8 (62.5)	8.8	24.4	45.4	68.2	100.2	183.0	485.6
Dismantling	864	67.3 (2.0)	89.2 (95.6)	9.1	25.9	44.8	63.5	95.9	221.5	850.5
Transporting materials	169	55.6 (2.2)	78.3 (95.3)	12.7	18.6	30.2	55.8	87.1	214.7	950.6
Other	110	50.7 (1.8)	58.7 (32.5)	10.1	19.4	34.6	52.4	76.1	114.8	220.1
Buy, sell, weigh	61	44.6 (2.3)	61.0 (49.5)	10.6	12.8	22.4	59.1	80.0	156.4	237.1
Repair	3	41.1 (1.1)	41.1 (2.8)	38.6	38.8	39.6	40.7	42.4	43.8	44.1
Non-work-related events	3311	57.5 (2.0)	72.7 (62.8)	4.0	16.4	37.4	61.0	90.5	161.7	1296.9
Smoking while sitting	210	66.9 (2.2)	90.8 (85.7)	6.0	13.5	42.1	68.3	111.2	219.8	685.3
Eating or drinking while sitting	201	62.6 (1.9)	80.1 (77.1)	11.2	25.6	41.1	61.0	90.7	195.0	687.7
Other	64	59.6 (1.9)	72.7 (48.0)	14.1	20.8	35.4	65.0	89.2	153.4	254.2
Sitting	2836	56.5 (2.0)	70.9 (59.7)	4.0	16.2	36.9	60.1	88.9	156.1	1296.9
Transportation-related events	1171	58.1 (2.0)	73.7 (59.7)	3.1	18.3	37.7	59.2	92.1	174.5	679.5
Walking	807	62.9 (2.0)	79.8 (63.8)	3.1	18.2	42.7	62.6	99.3	188.1	679.5
Bicycling	115	50.4 (1.8)	60.4 (42.0)	14.7	19.4	35.3	50.4	76.4	123.3	281.4
Motorbike or car	249	47.9 (1.9)	60.0 (49.2)	10.8	18.2	29.0	49.0	75.2	135.3	479.0
Total[b]	6239	60.2 (2.1)	80.6 (92.9)	3.1	18.6	38.2	61.0	92.5	186.2	1501.4

[a]Activities used in this table were derived from image-based time-activity patterns.
[b]Out of a grand total of 7121 five-minute averaged intervals, 6239 were used after excluding n = 629 five-minute intervals that were unusable due to removal of the sampling backpack by the participant; n = 114 five-minute intervals taken in the staging area where devices were turned on and off and participants completed registration; and n = 139 five-minute intervals recording PM levels on a day with an adjacent urban fire.

Discussion

Wearable camera images can improve time-activity data in an unorganized work environment with substantial occupational exposures. Using images to generate an objective source of high-resolution time-activity data greatly reduced participant burden, a strength of this study. The use of image-based TAPs combined with continuous and contemporaneous measures of size-specific PM estimates provided a unique data set from which high-risk job activities and modifiable work behaviours, such as socializing and eating near hazardous work tasks, were identified. Notable findings included high variability in the type and duration of e-waste recovery tasks performed by a worker per shift and over time; poor agreement between self-reported and image-based time-activity data; the highest mean personal $PM_{2.5}$ exposures occurring during burning activities, driven by short-term, peak exposures, followed by sorting and dismantling; $PM_{2.5}$ exposures during long periods of non-work-related activities exceeded the WHO standard in 88% of measured data.

Improved methods for collecting time-activity data

Improved methodologies for collecting accurate time-activity data in challenging informal work settings are needed. In addition to misclassification, social-desirability, and participant fatigue, standard time-activity diaries collected in informal sectors may be limited by language and literacy challenges and the lack of routines and organizational structure in which recall can be grounded (Hunt and McKay, 2015). A recent trend to improve personal exposure estimates in large population-based studies with more precise time-activity data has led to the use of location tracking technologies including smart phones and global positioning system (GPS) devices (Ouidir *et al.*, 2015; Glasgow *et al.*, 2016; Milà *et al.*, 2018). The quality and relevance of such data depend on many factors (e.g. phone technology, wireless provider, network coverage, and the amount of time the phone is kept on) that are particularly problematic in low- and middle-income countries (Glasgow *et al.*, 2016). GPS data often

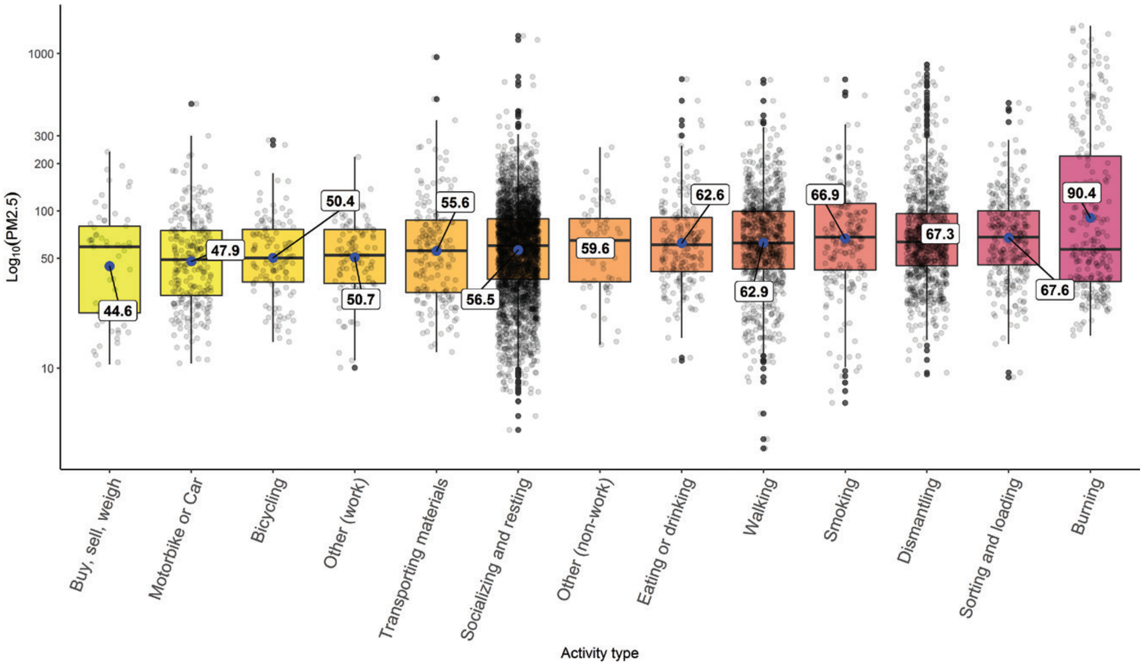

Figure 3. Personal inhalation exposure to $PM^{2.5}$ by activity type (image based) and sorted by ascending geometric mean. For each boxplot, the midline represents the median value and the labelled blue point describes the geometric mean. The upper and lower limits of the box represent the 75th and 25th percentiles, respectively. The 'whiskers' extend to 1.5 times the interquartile range from the top and the bottom of the box. The points beyond that distance are represented by individual points. The jittered black points show the density of data by activity; each point represents a 5-min $PM_{2.5}$ average value.

require extensive cleaning particularly in dense urban areas and indoors (Ouidir *et al.*, 2015). As an alternative, wearable cameras, most commonly the 'SenseCam', have been used to improve memory recall, enhance the assessment of physical activities detected by an accelerometer, and classify environmental characteristics and health behaviours (Doherty *et al.*, 2013; Mavoa *et al.*, 2013; Oliver *et al.*, 2013). Wearable camera data are also time intensive for the researcher, but can represent an improvement over GPS for the purpose of job identification in informal sectors since the location of a job may change dramatically from day-to-day. Additionally, they eliminate the participant burden and literacy requirements associated with workers keeping active time-activity diaries with 5- or 15-min resolutions; such high-resolution diaries may be required in job settings with frequent task changes and acute exposures.

Other work has been used to match images and videos with exposure measurements. In a peri-urban Indian environment, Salmon *et al.* (2018) used wearable cameras combined with personal $PM_{2.5}$ monitoring (Salmon *et al.*, 2018). Similar to our results, the high time-resolution of the images afforded the ability to detect short-term, peak exposures and revealed activity–exposure relationships not captured in self-reported diaries (Salmon *et al.*, 2018). In an office building, Luoma and Batterman (2001) used stationary video recordings in combination with area pollutant monitoring to characterize changes in emissions due to recorded work activities (Luoma and Batterman, 2001). On formal construction sites, video recordings have been used for tracking job progress, personnel, and safety monitoring; however, development of automated methods for object identification and tracking are still being developed (Teizer and Vela, 2009; Chi and Caldas, 2011).

The methodology in this article to derive image-based TAPs from wearable camera images as a tool to improve occupational exposure assessment proved effective. The TAPs represented the natural flow of activities during a work shift, provided a sufficient level of detail with an interval of only one photo per minute, documented visual details relevant to inhalation exposure and potentially other stressors (e.g. ergonomic), facilitated the estimation of task-specific exposure concentrations, and enabled the transformation of processed image data into a standard time-activity diary of any time resolution that is compatible with standard risk assessment methods. Prior knowledge of e-waste work activities was required to process the images;

however, previous literature, field visits, and unstructured interviews with workers provided sufficient information.

Self-reported and image-based time activity

Participants reported performing multiple jobs at any given time during their employment at Agbogbloshie. These results are similar to those in previous studies among the same population (Feldt *et al.*, 2014; Burns *et al.*, 2016; Srigboh *et al.*, 2016). The image-based TAPs agreed with the self-reported data with respect to the types of job tasks most frequently performed on-site with the exception of buying, selling and non-work-related activities as per Tables 1 and 2 and Supplementary Table S4. The poor observed agreement between self-reported and image-based data from a subset of participant diaries, confirmed that self-reported diaries cannot achieve the degree of task and time precision needed to detect changes in a measured exposure over intervals of five, ten, or even fifteen minutes or distinguish groups of workers on the basis of their exposures and subsequently occupational risks. Diaries may improve survey instrument development by broadly characterizing tasks workers perform (or intend to perform given the availability of materials).

Personal inhalation exposure to $PM_{2.5}$

Worker tasks associated with peak $PM_{2.5}$ exposures were easily identified using the image-based TAP data. In addition to the specific task itself (e.g. burning), worker movements while transporting e-waste in and out of the fire or periods of variable wind direction and speed may also contribute to high exposure levels. Lower exposures probably occur while workers are positioned upwind of the fires and other emission sources and on days with steady winds (Supplementary Fig. S5, available at *Annals of Occupational Hygiene* online, provides images depicting upwind and downwind exposure scenarios).

Personal inhalation exposure during non-work activities is comparable to those during non-burning e-waste recovery tasks. In 43% of the images (n = 15) from sitting and eating activities with $PM_{2.5}$ exposures exceeding 448 µg m^{-3}, flames and smoke were identified objects. The location of activities in relation to the source of emissions from burning activities appears to greatly contribute to a worker's $PM_{2.5}$ exposures. The ranking of median exposures by activity further suggests that on days with low variability in wind direction, burners may actually be able to control their exposure in contrast to people doing most or all of the other work that are downwind of burning activities. For sites with a prevailing wind direction, such as Agbogbloshie, relocating work activities to areas typically upwind of burning activities, may markedly decrease personal inhalation exposures for those workers. However, this type of site reorganization may increase exposure among residents living in the densely populated communities located on all sides of the site.

Limitations

The use of wearable cameras in research can come with ethical (Kelly *et al.*, 2013) and analytic limitations (Doherty *et al.*, 2013; Salmon *et al.*, 2018). In occupational settings, camera use is less invasive to an individual's privacy than in home settings. Non-compliance among participants resulted in the exclusion of 9% of the data. The coding process and reviewer training were significant time commitments. Advancements in the use of artificial intelligence and machine learning for image-processing may overcome this burden and introduce new opportunities for exposure science in a world of big data (Weichenthal *et al.*, 2019). The test of agreement between self-reported and image-based activities was limited by differences in how a worker and image-reviewer report activities with multiple sub-tasks (e.g. collecting). However, an individual's natural reporting tendencies may actually 'interfere' with achieving exposure and health-related objectives. Tasks that are verbal in nature (e.g. buying or selling) may have been misclassified as non-work activities (e.g. sitting), however, may also be associated with fewer occupational hazards. Including exemplar images of sitting activities in the worker interviews may have improved classification of these verbal activities. Double-data entry or having a reviewer familiar with the site could reduce activity misclassification. With limited resources for double-data entry, we minimized event misclassification with recurrent trainings and worker interviews.

Activity-specific $PM_{2.5}$ estimates are descriptive only and have not been adjusted for ambient $PM_{2.5}$, location, wind, other meteorological factors, or the repeated nature of the study design. We did not exclude 0.2% of the data in which $PM_{2.5}$ estimates exceeded the particle counter's upper concentration range (1000 µg m^{-3}). The true concentration was likely higher than the reported measurement, particularly for fine fraction PM (e.g. $PM_{2.5}$). We compared the $PM_{2.5}$ after removing the values >1000 µg m^{-3} with the full data set and found no statistically significant difference (Mann–Whitney P-value: 0.7921). 'Unusable' images, which were associated with lower $PM_{2.5}$ estimates than in the rest of the data, had to be excluded to avoid misclassification bias. Removed bags were placed by the workers into 'safe' or isolated locations, which may be responsible for lowering their associated $PM_{2.5}$ concentrations. Findings from the partial-shift samples are representative of all three seasons in Accra (dry, wet, and windy), but only during the morning and afternoon hours during which participants wore the backpacks. Last, a possible 'drift' in synchronized device clocks could cause measurement error when examining the association between instantaneous measures (Doherty *et al.*, 2013).

Planned future work

Planned future work will use $PM_{2.5}$ concentrations and paired activities to establish epidemiologic evidence with regard to potentially associated health outcomes, particularly acute responses such as cross-shift changes in pulmonary function. The images highlighted an area of future research, specifically the health effects among women on-site working near burning activities—we observed women selling water to e-waste workers for the purpose of cooling recovered metal after it is removed from the fire. Additionally, studies are needed to address the observed under-employment among other psycho-social job characteristics, such as job stress, limited upward mobility, and effort-reward imbalances experienced by this population (Burns *et al.*, 2019). Psycho-social factors are predictive of mental and social functioning disorders, cardiovascular disease risk factors, coronary heart disease, and musculoskeletal disorders (Cohen *et al.*, 1983; Karasek *et al.*, 1998; Siegrist, 1996) and may independently affect or moderate the health effects caused by the physical exposures. Future proposals to reorganize the worksite and worksite methods should involve an iterative process between workers, local leaders, and multidisciplinary teams, including engineers, exposure experts, epidemiologists, and social scientists, and improve conditions for both workers and surrounding communities. The images can subsequently be used in training materials.

Conclusions

The International Labour Office (2018) estimates that informal employment accounts for 86% of all employment in sub-Saharan Africa and 62% globally (International Labour Office, 2018). The undocumented nature of this informal sector, in which men and women face substantial occupational health and safety hazards without physical, social, or economic protections, requires innovative and adapted methods for understanding workers' needs and sources of hazards. Wearable cameras provide a strong alternative to standard recall- and observational-based methods of recording time-activity and reduce participant burden. The use of wearable cameras to improve occupational exposure assessments and provide strong evidence of the risks informal workers experience has broad implications for the improvement of the health and well-being among too many unprotected workers around the globe.

SUPPLEMENTARY DATA

Supplementary data are available at *Annals of Work Exposures and Health* online.

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Disclaimer

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