Does commuting really make a difference in my steps? Examining walking experiences of hybrid workers.

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Introduction & Motivation

COVID-19 has changed the way we work. Instead of commuting to the office each day, office workers work remotely from home, or reduce the number of days in the office to a ‘hybrid’ schedule, where workers go in person a limited number of days per week (Parker et al., 2020). Studies on the sedentary behavior of office workers before the COVID-19 pandemic occur in the context of in-person office environments. Evidence exists that sedentary lifestyles are associated with poor health outcomes, including but not limited to obesity, cardiovascular disease and high blood pressure (*Health Risks of an Inactive Lifestyle*, 2021).

With the shift in working environments from principally in office to at home, we aim to examine the walking patterns and perceptions around walking for in-person and remote working environments. Our collected data will elucidate similarities, differences, and nuances in the experience of walking between different work environments.

Related Work & Background

Past studies examine the relationship between remote work and sedentary behavior. Using survey data, researchers at the Stanford Center for Longevity (Streeter et al., 2021, pp. 1–11), found that remote work led to two more hours spent sitting down per day. Researchers did not however find a significant relationship between working from home and inadequate exercise. Using the Sedentary Behavior Questionnaire, researchers at the University of Pittsburgh (Barone Gibbs et al., 2021, pp. 86–90) found that shelter-at-home mandates led to a 1.3 hour increase in non-workday sedentary behavior, but that there was no significant effect on workday sedentary behavior. (Stephenson et al., 2017, pp. 1–8) found that computer, mobile and wearable interventions significantly reduced sitting time by ~41 minutes per day. During long-term follow-ups (>6 months) the reduction had dropped to ~2 minutes per day on average.

Pre-pandemic studies demonstrate technology-based interventions to motivate office workers to walk including break reminders (Luo et al., 2018) and gamification (Lin et al., 2006). Prior work recommends supporting the user to set their own goals as opposed to prescribing a number or range, to consider abstract visualizations in addition to graph visualizations for walking data (Fan et al., 2012), to credit users for their incremental success, make collected data available on activity level for reflection, support the social networks, and to integrate considerations of practical and logistical constraints into system design (Consolvo et al., 2006). Embedded into the practical considerations, activity tracking technologies should be context-aware, that is, to consider the working environment and mitigate foreseen barriers to use (Damen et al., 2020). As such, our proposed study is an exploration of the working environment as it relates to walking.

In conducting studies on self tracking of walking, researchers are advised to be wary of the novelty and reactivity influences to the data (Harrison et al., 2014), and that people with less motivation fail to change their behavior in the long term (Gorm & Shklovski, 2016). Thus, our study design and analysis is constructed to minimize and account for novelty and reactivity influences.

RQ: How does the walking experience differ between a remote and an in-person working environment?

Our target population is hybrid workers.

Method

The study was designed as a pilot study using experience sampling method (ESM) to explore the walking habits of remote and in-person working environments.

Recruitment

We recruited 6 participants. Inclusion criteria for the study was access to an iPhone, willingness to enable and share activity tracking with Apple Health, work remotely at least one day in a two week period and work in-person at a workplace at least one day in a two week period. Both part- and full-time employees were included in the recruitment criteria. Any type of worker was included in the study. An exclusion criteria for our study was people with walking impairments. We recruited participants from their personal networks. There was no compensation for participating in the study. We sent a recruitment email to participants illustrating the requirements for participation (Appendix A).

Implementation

Prior to the start of the study, we asked participants to describe their typical working schedule including days, hours and work location to frame and anchor data collection. We sent the pre-study questionnaire (Appendix B) to participants via email.

Participants received two pings per day via text message, once in the first half of their work day and once in the second half of their work day. The ping contained a link to a Qualtrics survey with four questions (Appendix C). Figure 1 illustrates the implementation in qualtrics

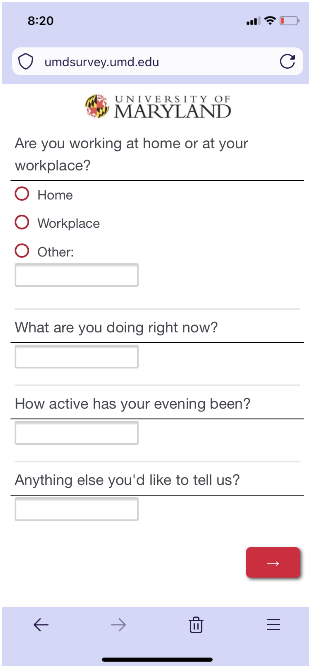

Figure 1. Survey questions

The ping questions were inspired by the International Physical Activity Questionnaire (IPAQ).22. Although participants received two surveys, three surveys exist to accommodate working schedules that occur in the morning, afternoon, and evening. The surveys reflect linguistic contextual differences, “How has your (morning/afternoon/evening been)?”.

Employing a random sampling method, the time at which the pings were sent was randomized within the two time buckets of first half of participant’s work day and second half of participant’s workday. The start and end times of participants’ workdays were collected via the pre-study questionnaire. The second ping occurred at least one hour after the first ping. Because the pings came as text messages, the notifications did not expire. We used the Shortcuts app on the iPhone to automate text messages as illustrated in Figure 2 and Figure 3.

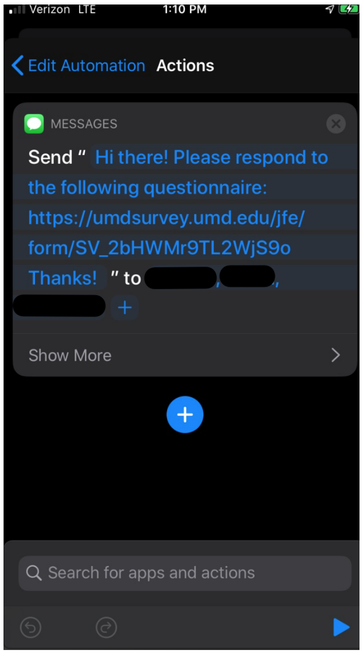

Figure 2. The automated text

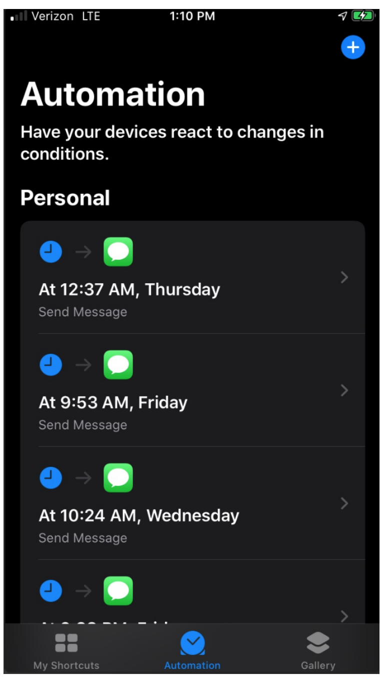

Figure 3. Matching Automation to participant schedules

We sent the participants the instruction manual at the end of the study to share their health data. Participants shared their activity health data with us by downloading and sending a zip file of their activity data via email to us. The Apple Health activity data on the iPhone included information on steps to ground participant responses in their automatically recorded walking activity.

We sent the participants the instruction manual at the end of the study to share their health data along with an email (Appendix D). The questionnaire was created using Qualtrics. Sample implementation questionnaire distributed via iPhone Shortcuts app (responses were discarded prior to pilot).

We created templates on the Shortcuts app for each of the times (morning, afternoon and evening).We piloted the implementation to ensure that the Shortcuts app sent scheduled messages in an appealing format and that the questionnaire service records responses. The timing was completed by using the https://www.random.org/clock-times/ within the two time boxes of the worker's day, and with the second text greater than one hour after the first.

Participants

We recruited 6 participants. Due to changing working conditions based on workplace COVID regulations, of the 6 participants original participants, only 4 participants qualified. Two participants began working in-person full time at the time of participation, despite having a hybrid working schedule at the time of recruitment. We informed the participants that they no longer qualified and excluded them from the study after the per study questionnaire and before beginning the pings. Descriptive information about the participants is present in Table 1.

	Commute mode	Physical demands of work	Working hours per week	Age	Job
P1	Car	Low	40 h	62	Legal Consult in Banking
P2	Car	Low	40 h	23	Receptionist
P3	Car	Low	20 h	25	Graduate Assistant
P4	Bus or Car	Low	20 h	24	Graduate Assistant

Table 1. Participant descriptions

Data collected

We collected data over a two week period and excluded data from non-workdays. Data compliance is depicted in Table 2.

	Pre study questionnaire response*	Response rate	Response %	Health data shared
P1	Yes	15 of 20	75%	Yes
P2	Yes	16 of 16	100%	Yes
P3	Yes	6 of 12	50%	No
P4	Yes	12 of 20	60%	Yes
Overall	4 of 4, 100%	37 of 68	54.4% (rounded to nearest .1%)	3 of 4, 75%

**P5 and P6 responded to the pre study questionnaire and were excluded based on their responses*

Table 2. Data compliance

Due to suboptimal survey design (text response boxes were not large enough), P3 responded a few times to the same ping. The participant informed us and we improved the survey format. The latest (time stamp) response will be included and the earlier responses will be discarded (only a few minutes in between each response). We reached out 3 times for P3's health data and did not receive a response.

Data quality varied from participant to participant and response to response. For example, one response with low quality was "Not very active" when compared to "Not very because I have to work but I think I get more steps in at the office because distance to kitchen, copier, restrooms. Also standing talking to coworkers. Hope to go for a walk on the way back from work.".

Data analysis

We aggregated each participant's responses to the pings and iPhone activity data. We used Apple Health XML to CSV Converter to organize the step count data (https://www.ericwolter.com/projects/apple-health-export/). We produced descriptive statistics and examined the step count data in relation to the working environment. Within each participant, we examined the number of steps per day in relation to their working environment. We contextualized the questionnaire responses by noting the working environment and deviation from the average amount of steps of that participant as depicted in Figure 4.

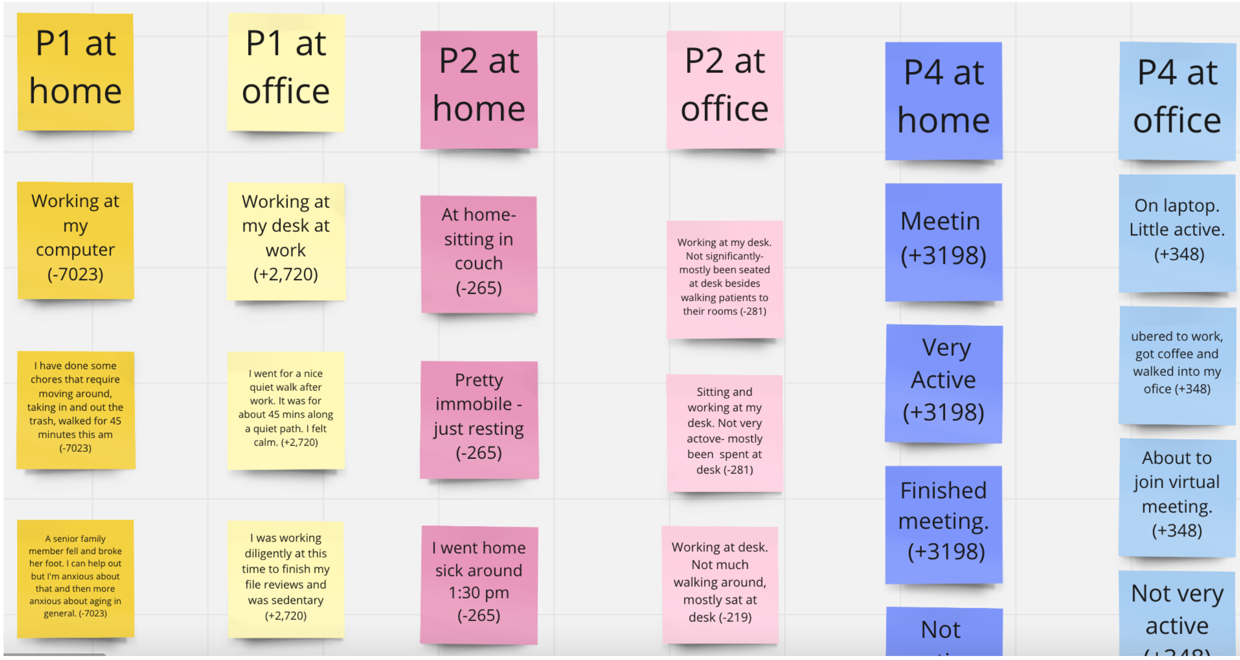

Figure 4. Excerpt of organization and contextualization of qualitative data

Codebook

We organized the data into categories using a codebook approach. Codes are Location, Activity influencers, Perceived activity level, Wellness, Mode of transit to work, Physical activity and Study design as illustrated in Figure 5.

Figure 5. Codebook initial codes

Results

Table 3 depicts the descriptive statistics of the average and standard deviation of the step counts for in-person and remote working days. Figure 6, 7, and 8 are the step counts for in-person vs remote days for participants. Figure 9 is the combined average step count for each participant for their remote versus in-person days.

Location	Mean ± SD		
	P1	P2	P4
In-Person	7158.8 ± 4165	1259.8 ± 244.5	6589 ± 3119.2
Remote	8417.3 ± 2754.2	1214.5 ± 326.0	4795 ± 6214.1
Overall	7913 ± 3295.3	1248.5 ± 241.5	5991 ± 33797.2

Table 3. Descriptive statistics

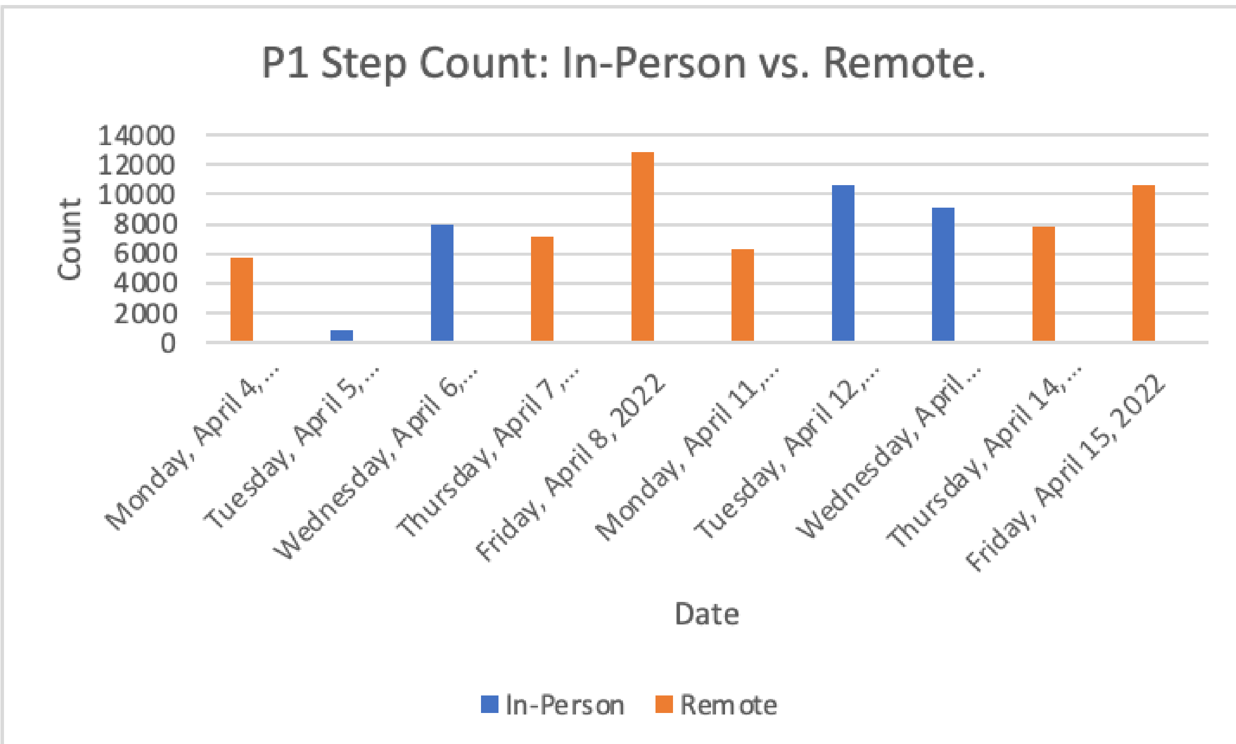

Figure 6. P1 step counts for in-person versus remote working days

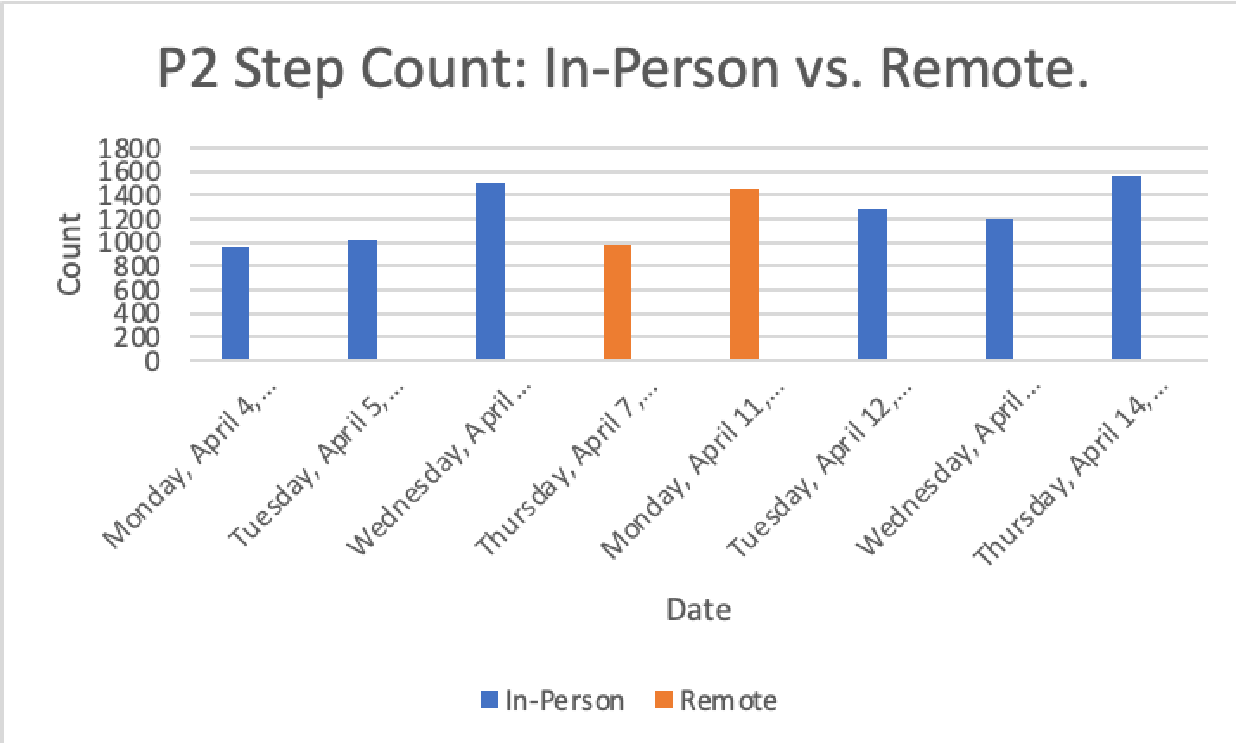

Figure 7. P2 step counts for in-person versus remote working days

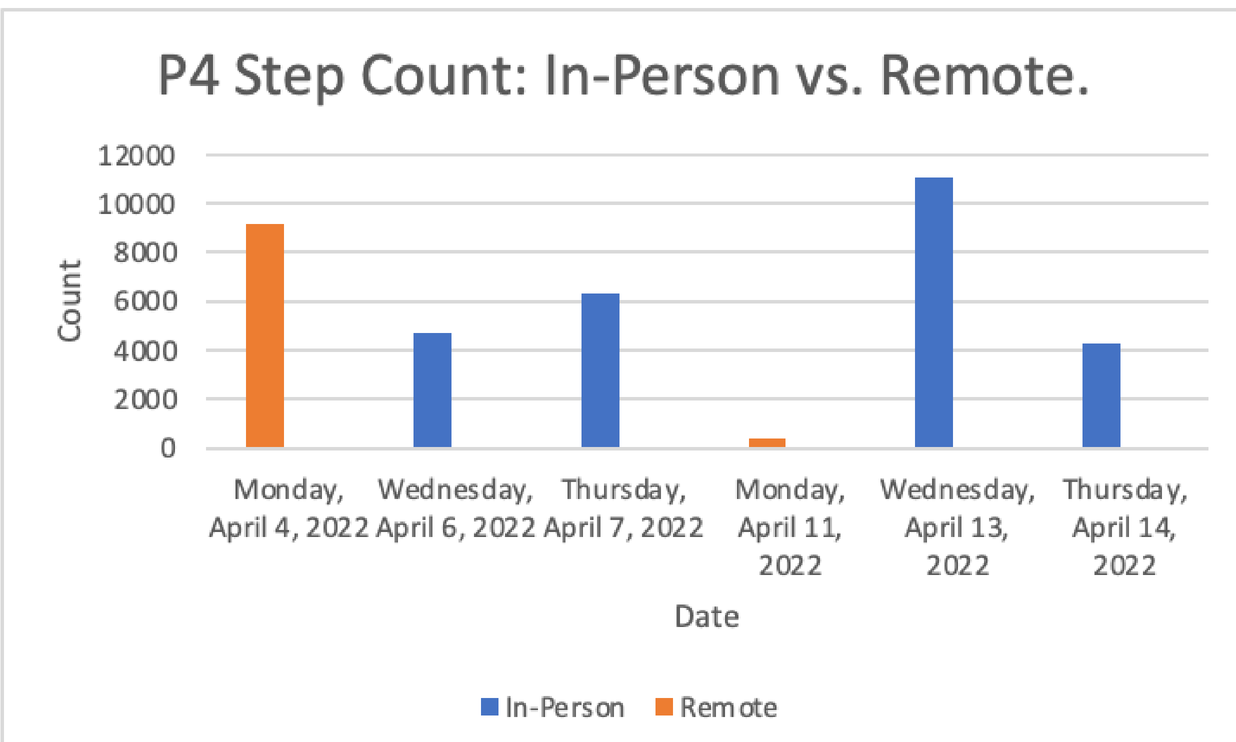

Figure 8. P4 step counts for in-person versus remote working days

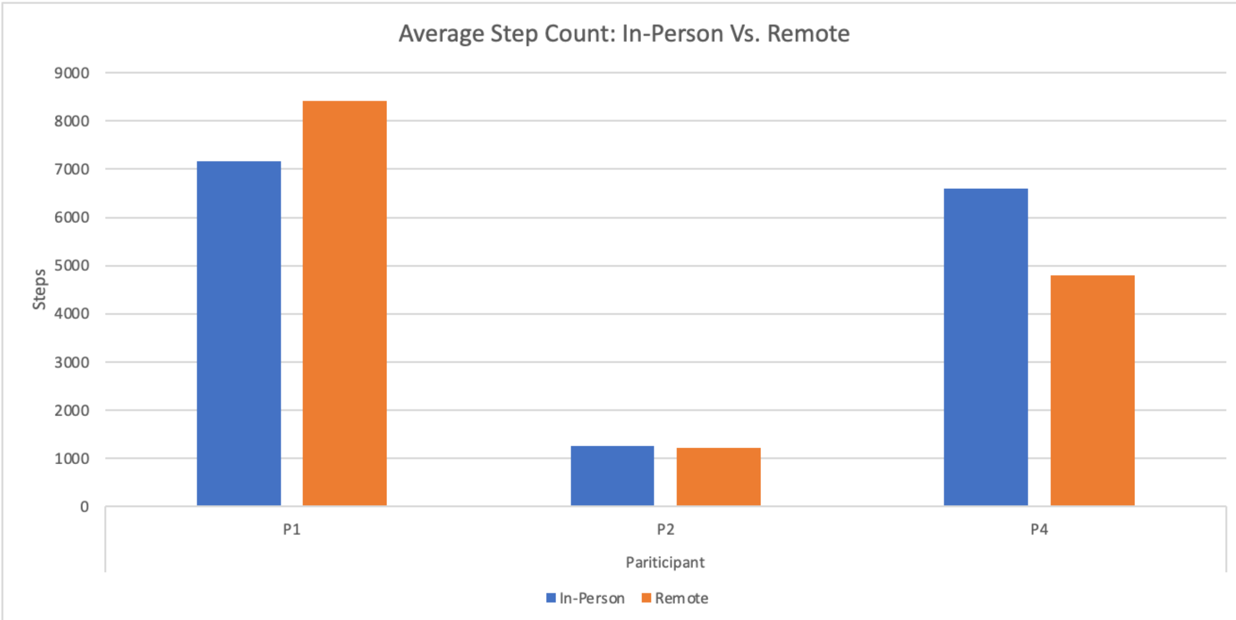

Figure 9. Combined average step counts for each participant

Discussion

Participants showed a range of walking behaviors

In our sample, we had one participant who walked more on remote days, one who walked more on in-person days and one whose walking on both days was virtually identical. While we can not arrive at any statistical conclusions based on such a small sample. It is interesting to note the diversity.

Activity perceptions don't always match step count

There are instances when the number of steps is at odds with the participant's reported activity level. During one of P1's work from home days, they report "I have not been active this afternoon, been busy with work", despite having taken 4,934 steps more than P1's average over the study period. The difference could be due to the study design and the analysis, as the participants could have walked after responding to the ping. A possible improvement could be to collect only one response per day, at the end of the day on the participant's overall activity level.

In person work as a driver to activity

In person work required P2 to move around "*Been up walking back and forth with patients more frequently this afternoon so a bit more active than usual.*". On this day, P2 had about an average number of steps (47 less than average). P2's working tasks required her to move around indicating that in-person work can be a driver for activity. In-person work activities could be designed to be active, such as encouraging walking meetings, stand ups where people actually stand up, or encouraging employees to walk during breaks. The size and design of the physical workplace along with the work tasks can facilitate activity.

Workload (both in-person and at home) as a barrier to activity

Work in general acted as a barrier to activity P1 noting that she is more active since she is out of work early, and noting that she is not very active when she is at her desk. She has trouble taking walks if she's fallen behind on her work, since she must remain at her desk to complete her work. A reduction in workload may help people to allocate more time to activity as opposed to working promoting overall wellness of employees.

Activity outside of workday

Aligned with prior work from Stanford Center for Longevity (Streeter et al., 2021, pp. 1–11) that notes that working from home was not linked with inadequate exercise, despite working from home, our participants noted activity that occurred outside of their workday.

"I was able to go out to exercise, walk/ jog for 45 minutes, and do my stretching and strengthening exercises. I may be getting out of work early and I hope to walk more." (P1, working from home,2,697 steps more than average)

When assessing activity, there is activity during the workday and before and after the workday. Remote workers find time to exercise when perhaps they would be commuting in their car if they were in-person.

Weather as an activity influencer

Participants highlighted weather changes in their reports on their activity levels indicating that weather influences activity whether they are in the office or at home.

"Did my regular workout. The weather is nice for exercising outdoors." (P1, working from the office, 1,243 steps than average)

Applications aimed at increasing the activity levels should consider weather when prompting users to walk. For example, if it is raining outside during the morning and the rain stops in the afternoon, the app could encourage the user to walk.

Sickness as an activity barrier

P2 became sick during the study and her activity levels drastically reduced. To get better, she needed to rest. In the design of technologies that promote activity levels, wellness should be considered as prompts to increase activity levels may be misaligned with overall wellness, and the need to rest when sick. Due to the in-situ nature of ESM, it is likely that life will happen during the study, whether that be sickness (P2) or family matters (P1). Designing studies for flexibility in participation (e.g., allowing participants to go back and fill in responses) lends to continued participation even when life events occur.

Motivation vis-a-vis reactivity

One participant notes that by answering the pings, she feels more motivation to go outside and walk.
"But even texting this I feel more resolve to get out." (P1)
Answering the pings about their activity levels made the participants aware of their activity. However, this is an example of reactivity, as the study design is changing the participant's behaviors, and we are measuring and studying said behaviors.

Reflections
To improve the study, the number of pings could be reduced to one per day as participants either worked in person or remotely, so one overall perception would be adequate for the day. In addition, we would allow for participants to go back and fill in their information if they wanted to, later in the day. Participants asked to be able to do this, and given the reduced number of pings to one, an improvement is to request one response recapping the activity for the entire day.

Limitations

Of the initial 6 participants we recruited we were only able to collect data from 3 of them.

Activity was measured using the participant's iPhones which may have biased our measures of their step count. In order to conduct this study we assumed that the participants would have their phone on their person enough to accurately reflect their walking habits. However, it is possible that the amount of time spent carrying a phone could vary greatly between different days. We relied on self-report to capture the other activity that can not be measured using the participant's iPhone. Potential improvement includes using a smartwatch that captures diverse activity types (e.g., cycling).

Future Work

Future studies could build on the work we have done by using a larger sample and if possible recording participants for longer periods of time. Doing so would increase the amount of data collected and allow researchers to conduct statistical analysis.

If participants are being studied for more time, measures need to be taken to reduce the burden on them. For example, there could be less pings each day (one a day, instead of two), and perhaps the ping could come at the end of the day when participants are not busy with work. Of course doing so could possibly increase recall bias but it is also important to keep participants engaged and responding throughout the study.

Conclusions

Based on the findings from this pilot study we were able to validate our methods as effective for capturing participant's walking habits. By combining qualitative responses to the survey with the step data, we were able to gain further insight into the various factors besides work environment that can impact walking habits. Future studies could use these factors to structure sampling questions, asking participants about their overall wellness, including if they felt ill.

Appendix

Appendix A Recruitment email
Subject: Graduate school pilot on walking habits of hybrid workers

Hi [participant name],

As a part of a graduate school program, we are piloting a study on the walking habits among people with hybrid work environments.

Length of the study:
- 2 weeks
- Sunday April 3 through Sunday April 17

Participation time requirements:
- ~10 minutes/day
  - 2 x 5-minute surveys

Requirements:
- [ ] Willingness to enable activity tracking on Apple Health on a personal iPhone
- [ ] Work from home at least 1 day in two week period
- [ ] Work in-person at workplace at least 1 day in two week period
- [ ] No walking impairments

With your consent, your activity data will be captured over the two weeks and we will ask that you share your activity data with the research team through Apple Health, an application already available on iPhones. Although all of your activity data regarding steps will be shared with the research team, only the two week period will be analyzed.

Are you willing to participate in our study?

Sincerely,

Caroline Berger & Mofe Barrow

Appendix B Pre-Study Questionnaire

1. What days of the week do you work?
2. What days of the week do you work remotely?
3. What days of the week do you work in-person at your workplace?
4. When do you begin work?
5. When do you end work?
6. Are there derivations to this schedule? If so, what are they?
7. How do you commute to work?
8. How long does it take you to get to work?
9. Describe how physically demanding your job is.
10. Anything else you'd like to tell us?

Appendix C Questionnaire throughout Study

1. Are you working at home or at your workplace?
2. What are you doing right now?
3. How active has your (morning/afternoon/evening) been?
4. Anything else you'd like to tell us?

Appendix D Request for health data email

Subject: Walking habits: Request for health data
Attachment: instruction manual
Hello,

Thank you for answering the questions over the past two weeks. As the final part of the study, we ask that you send your apple health data to cberger2@umd.edu. Please see the instruction set attached. If you have any difficulties feel free to call me at 617-981-9479.

Please send your data by Sunday afternoon.

The research team will only be extracting the step data from the supplied data. If you have any concerns please let us know.

Thank you,

Caroline

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