Understanding Personal Productivity

How Knowledge Workers Define, Evaluate, and Reflect on Their Productivity

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ABSTRACT

Productivity tracking tools often determine productivity based on the time interacting with work-related applications. To deconstruct productivity's diverse and nebulous nature, we investigate how knowledge workers conceptualize personal productivity and delimit productive tasks in both work and non-work contexts. We report a 2-week diary study followed by a semi-structured interview with 24 knowledge workers. Participants captured productive activities and provided the rationale for why the activities were assessed to be productive. They reported a wide range of productive activities beyond typical desk-bound work—ranging from having a personal conversation with dad to getting a haircut. We found six themes that characterize the productivity assessment—*work product*, *time management*, *worker's state*, *attitude toward work*, *impact & benefit*, and *compound task*—and identified how participants interleaved multiple facets when assessing their productivity. We discuss how these findings could inform the design of a comprehensive productivity tracking system that covers a wide range of productive activities.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

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KEYWORDS

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1 INTRODUCTION

Boosting productivity is important for creative knowledge workers (e.g., software developers, writers, researchers, designers). Self-tracking of personal productivity is a common technique to improve productivity [46] because it helps knowledge workers understand and reflect on how they spend their time. Productivity tracking technologies have become proliferated in our everyday life, supporting to track usage patterns at a device level (e.g., Moment [22], ScreenLife [44]) as well as an app level (e.g., RescueTime [43], TimeAware [27], meTime [52]).

Existing productivity tracking tools are usually not designed to capture the diverse and nebulous nature of individual workers' activities. Although the specifics of their day-to-day activities vary, existing technologies track activities that are easy to capture. For example, automated monitoring tools such as RescueTime [43] can capture activities that involve digital devices only, and thus calculate productivity based on software usage duration. Furthermore, prior studies often measured productivity (e.g., engagement [27, 55], performance [19]) within work contexts.

However, we have little knowledge on how people conceptualize *personal productivity* in both *work and non-work contexts*. In understanding personal productivity, considering both contexts is important: the distinction between work and non-work contexts has become fuzzy, as work slips into our lives, and activities in non-work contexts can affect productivity. In this work, we investigate what productivity means for individuals: what activities do knowledge workers consider *productive* and why? The findings could inform the design of productivity tracking tools that capture a comprehensive range of activities that knowledge workers engage in, going beyond the traditional measures of device usage time and app category.

In this paper, we present a diary study on personal productivity, collecting the activities that are perceived to be productive and their subjective productivity level (*neutral*, *productive*, and *very productive*), as well as individuals' rationale. We collected diary entries from 24 knowledge workers over the course of two weeks (10 weekdays + voluntary weekends), and conducted a semi-structured interview with them. Our participants recorded the productivity level of a wide range of activities, including both work-related and non-work related ones. From the analysis of diary entries, we identified six themes that characterize the assessment of productivity—*work product*, *time management*, *worker's state*, *attitude toward work*, *impact & benefit*, and *compound task*.

The key contributions of this work are twofold. First, we provide an empirical understanding of what knowledge workers account for when delimiting productivity-related activities and evaluating their productivity. Second, we offer implications for designing comprehensive productivity tracking tools that cover a wide range of *productive* activities.

2 RELATED WORK

Productivity has been of interests to diverse research communities. We first discuss the characteristics of knowledge work and traditional productivity metrics from the perspective of organizational psychology and human-computer interaction. We then review HCI research on factors influencing productivity and technologies designed to enhance productivity.

Measuring Knowledge Workers' Productivity

While there is no single definition of productivity that everyone agrees upon, productivity is commonly defined as the ratio of outputs over inputs [39]. In The Industrial Age, measuring productivity of a given person was relatively straightforward, as inputs (labor and capital) and outputs (tangible products) were easy to identify. In Information Age, measuring productivity of knowledge workers is more challenging than measuring that of traditional factory workers [18] because outputs are domain-specific and not easily quantifiable, and inputs are hardly standardized among different knowledge workers [40]. As such, developing performance metrics for knowledge work and maximizing knowledge worker's productivity have been an important topic.

Characteristics of knowledge work are different from those of traditional factory labor in terms of autonomy, uncertainty, and abstractness [1, 14, 17, 18]. For the large part of their job, knowledge workers autonomously choose and schedule their tasks, which can be assigned at unexpected time. A notion of *creative knowledge work* emphasizes the importance of creative skill sets—such as problem solving, problem seeking, idea generation, and aesthetic sensibilities [31]. In Reich's description, creative workers produce innovative goods in the knowledge economy [41].

Organizational productivity research has also examined the factors that influence employee productivity (see [20] for a review), including organizational factors (e.g., job characteristics [6], feedback [16], autonomy [16, 47], office environments [10]), as well as individual factors (e.g., intrinsic motivation [19], psychological well-being [10, 48, 53], work engagement [2, 55]). For example, a work environment promoting both autonomy and responsibility is likely to motivate their employees to yield positive work outcomes, such as work performance and job satisfaction [19].

The HCI community has studied knowledge workers' productivity in their computerized work environments. With the goal of identifying the source of distraction and interruption, researchers examined the nature of distractions and their effects on the work process [4, 12, 13, 23, 33, 34]. For example, Czerwinski and colleagues examined the nature of information workers' task switching, and identified factors—such as task complexity, task duration, length of absence, number of interruptions, and task type—that influence the perceived difficulty of returning to tasks. In a recent study, Mark and colleagues found that those who reported being less in control of their work, associated with personality traits of lower Conscientiousness and Lack of Perseverance, benefited the most from a system that blocks online distractions in the workplace [33]. In contrast to the prior approach of capturing pre-defined productivity metrics, we take an inductive approach to have a deep understanding on how knowledge workers conceptualize their productivity in both work and non-work contexts.

Enhancing Personal Productivity with Self-Tracking

We see a growing body of literature on productivity tracking technologies designed to help people track their productivity to improve self-awareness, which could lead to enhanced productivity [21, 27, 37, 38, 44, 52]. Because information devices (e.g., computers, smartphones) have become an integral part of people's work, as well as a source of distraction, many productivity tracking systems enable people to record device usage behaviors to provide insights into their usage patterns. Some systems consider screen time as distractive, thereby restricting specific apps (e.g., [26]) or locking smartphones for a specified duration (e.g., [25, 29, 30]) when people need to focus on their tasks.

These systems predominantly incorporate automated tracking, and thus rely on the relatively simple measurements that can be captured. For example, many of these tools capture the usage duration of each application (e.g., [21, 27, 32, 43, 52]) or the device (e.g., [44]), and some of them calculate a productivity score derived from the ratio of productive application usage to total computer usage [27, 43]. Commercial tools for developers' productivity usually track a developer's programming activities such as interactions with the integrated development environment (e.g., [11, 51]).

Although automated tracking reduces the capture burden and collects behavioral data with high granularity, this approach has three main limitations. First, automated tracking does not capture productive activities that people do without devices (e.g., ad-hoc meeting). Second, automated tracking does not always correctly infer a person's intention of using applications, websites, or devices. For example, people can use a video chat application (e.g., Skype, Hangout) or visit an online shopping site (e.g., Amazon, Ebay) both for work and for personal purposes. Most importantly, the duration of the app use is not reflective of a person's perceived productivity. For example, working on a Word document for a long time may not be an indication of productive writing. In this light, we need to understand how people assess their own productivity and incorporate them in the design of productivity tracking systems. We thus set out to collect self-reported data on activities that are perceived to be productive, along with contexts and their reasoning through a diary study.

3 DIARY STUDY

Capturing *in-situ* data on events and experiences is an ecologically valid way to understand people's daily lives. One commonly used technique is a *diary study*, a data collection method with which researchers ask participants to record a log of their receptiveness or circumstantial information close to the occurrence of a target situation [3]. To understand how people perceive and evaluate the productivity of their activities, we conducted a 2-week diary study using a mobile self-tracking tool followed by an exit interview. The study was approved by the institutional review board, and conducted in South Korea.

Participant		Occupation	Participant		Occupation
P1	46 (M)	Professor	P13	37 (F)	Clerk
P2	29 (M)	UI designer	P14	32 (F)	Medical writer
P3	44 (M)	CEO	P15	25 (F)	Clerk
P4	27 (M)	Interaction designer	P16	25 (F)	Interaction designer
P5	27 (M)	Developer	P17	29 (F)	Project manager
P6	30 (M)	Ph.D. student	P18	35 (F)	Clerk
P7	36 (M)	Project manager	P19	46 (F)	Counsellor
P8	26 (M)	Developer	P20	25 (F)	Ph.D. student
P9	28 (M)	Researcher	P21	33 (F)	UI designer
P10	28 (M)	Ph.D. student	P22	26 (F)	UI designer
P11	23 (M)	Ph.D. student	P23	35 (F)	Counsellor
P12	30 (M)	UI designer	P24	27 (F)	Interaction designer

Table 1: Demographics of the participants.

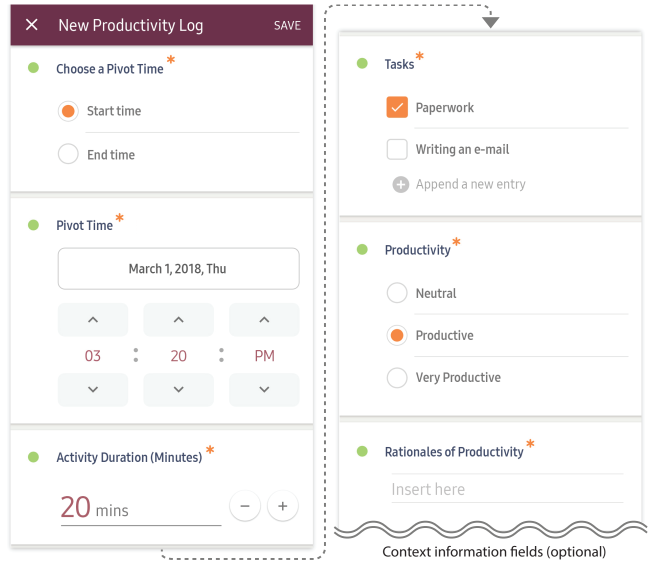

Figure 1: Mandatory fields in Productivity Journal. In this example, *paperwork* activity started at *3:20 PM*, lasted for *20 minutes*, and was evaluated as *productive*.

Participants

We advertised our study on social media and the alumni community website of a local university. Our inclusion criteria were adults who are: (1) working at least for 30 hours per week for their primary job; (2) not currently participating in other studies requiring self-reported data collection; (3) not an undergraduate student; (4) using an Android smartphone (our diary study tool supported Android only); and (5) interested in their personal productivity. Of the 48 people who filled out the screener, we recruited 28 people who met the criteria. As a minimum requirement for study completion, we instructed the participants to capture logs for a minimum of seven (out of ten) weekdays. During the deployment, one participant dropped out due to a health issue. Additional three were excluded during the analyses because they did not meet the minimum logging requirement.

In the end, 24 participants (12 female and 12 male; referred to as P1-P24; Table 1) completed the study. Their ages ranged from 23 to 46 (M = 31.20). They reported that they work for an average of 43.2 hours per week. Eleven occupations were represented among our participants, and three participants reported that they had a second job: one was a translator and the other two were managing their own online stores. We offered 50,000 KRW (about 45 USD) for their participation.

Study Instrument for Data Capture

We instructed participants to record the activities that they considered to be better than "unproductive" (i.e., *neutral*, *productive*, and *very productive*) in both work and non-work contexts. To identify what constitutes productivity inductively, We encouraged participants to freely define their own productivity, including the activity type and granularity, and rate the level of productivity. We did not ask to capture unproductive activities because (1) we were mainly interested in what activities are considered productive and why, and (2) we wanted to lower the capture burden. In addition, logging only positive tasks can be rewarding and thus help us further ensure adherence [45].

We deployed a mobile diary, called "Productivity Journal" (Figure 1). We created the diary app with OmniTrack [28], a mobile self-tracking platform that enables the creation of a tracking app by configuring an input schema and reminders on a mobile phone. For each productive activity, we wanted to capture the time stamp and duration of the activity, task details (e.g., paperwork, email, brainstorming, meeting), perceived productivity level (i.e., neutral, productive, very productive), and rationale for the productivity assessment (e.g., why a certain activity was rated "very productive"). We also included optional fields to cover contextual information such as devices used for the task, location, mood, and photo.

In the mobile app, participants could review their entries through a list and access simple visualizations (e.g., a daily entry count). A shortcut button on the smartphone's notification drawer and lock screen enabled participants to open the entry input screen instantly, and served as a visual reminder to enhance tracking adherence [8]. Details of the mobile app UI are described in [28].

In addition to Productivity Journal, we deployed another journal (called "Skip Journal") so that participants can report reasons when they did not capture any productive activities during the day (e.g., too busy to capture productive activities, did not do any productive activities). At 9:00 p.m. every weekday, the Skip Journal app sent a notification to participants if they did not log an entry in either of the two journals.

Procedure

Participants attended an hour-long pre-study session in a small group (2–4 participants), during which we explained our study goal and protocol. After installing the two diary apps (Productivity Journal & Skip Journal) on their smartphones, we gave a short tutorial on how to record and manage the journal entries. We instructed the participants to record the journals for two weeks (10 mandatory weekdays and 4 voluntary days in weekends). We emphasized that the number of journal entries is not tied to the study compensation. Starting a day after the pre-study session, the journal entries were uploaded to our server when participants' smartphones were connected to the network.

After two weeks, we met each participant individually for a debriefing session, which comprises a semi-structured interview and another activity that is outside the scope of this investigation (we do not report the data from this activity here). Each session lasted about one and a half hours, and was audio-recorded and transcribed. We asked questions regarding their logging contexts (e.g., "In what situation did you log an entry?"), assessment on productivity perception (e.g., "When did you feel productive?"), and insights gained from the tracking (e.g., "What did you learn about your productive activities through tracking?").

Data Analysis

From Productivity Journals, we first examined journaling patterns such as the number of entries and duration of the activities. We did not analyze the data from Skip Journals because they contained too few entries (only seven entries by six participants).

To understand participants' reasoning of productivity evaluation, we analyzed the open-ended answers in the *rationale* fields. Following the thematic analysis approach [5], three authors independently coded a subset of the entries (200 entries; 24%) to identify emerging themes regarding factors involved in the productivity assessment. As rationale can include more than one theme, we multi-coded the entries. After reaching an agreement in the coding scheme (Table 3) by resolving discrepancies in coding through multiple sessions of discussion, one researcher coded the remaining data.

To identify task categories of productive activities, we categorized unique task names found in the *tasks* fields. We referred to the answers in the *rationale* fields and the interview transcripts to disambiguate what participants actually did for tasks with a vague name (e.g., 'etc.'). We iteratively developed task categories and sub-categories. After identifying all task categories from our dataset, we finalized their names so that they are compatible with the task category names in Czerwinski and colleagues' work [12] (e.g., *project*, *routine task*, *email*, and *personal*).

4 RESULTS

We report the results of our study in three parts: (1) descriptive summary of diary entries; (2) rationales for productivity evaluation; and (3) task types of productive activities.

Descriptive Summary of Diary Entries

During the 2-week deployment, we collected 830 Productivity Journal entries captured by 24 participants. The entries contained a total of 1,197 hours of activities. Of the 830 entries, 104 (12.53%) contained two or more tasks (indicating multitasking or multifaceted nature of the activity), and 752 (90.60%) entries were captured during the weekdays. In Table 2, we summarize the details about the entries captured in weekdays and weekends.

	Number of entries[a]	Avg. # of entries	Total duration
Weekdays	752 (262/312/178)	31.33 (N = 24)	1,063 hours
Weekends	78 (22/31/25)	4.87 (N = 16)	134 hours
Total	830 (284/343/203)	34.58 (N = 24)	1,197 hours

[a] Inside parenthesis: *neural*/*productive*/*very productive* entry count.

Table 2: Summary statistics of the Productivity Journal.

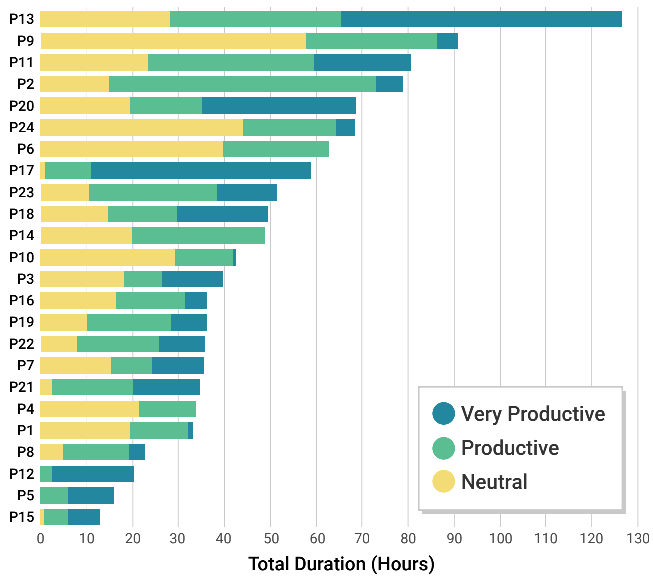

Figure 2: Total duration of the captured activities for each participant (grouped by the productivity levels).

Participants recorded entries for an average of 9.20 weekdays (SD = 1.10), with 14 participants recording all 10 weekdays. Although the weekends were optional, four participants completed all 14 days. Participants recorded an average of 49.88 hours of productive activities in total (SD = 26.66), and the entries from weekdays occupied 4.42 hours per day. However, there was a high interpersonal variation in total duration and the proportion of each productivity level (Figure 2). The average length of activity duration in each entry was 86.53 minutes (SD = 74.62), while 56.63% (470 entries) of the activities lasted no more than an hour. The average length of activity per participant ranged from 43.37 to 157.15 minutes. The number of unique tasks participants captured ranged from 2 to 17 (M = 8.83, SD = 4.15).

We note that participants might not have clearly excluded unproductive activities on their entries. Some entries with *neutral* label might have captured both the least productive and unproductive activities: we encountered several entries which mention the "unproductiveness" in their rationales. This might have affected our results to be a bit more inclusive for unproductive activities. However, given the qualitative nature of our study and such entries' relevance to productivity, the small number of such additional entries have minimal threats to the validity of our investigation.

Rationales for Productivity Evaluation

Analyzing the *rationale* field of the diary, we identified 21 subthemes of productivity evaluation which are grouped into six themes (Table 3). In the following subsections, we discuss each theme and contributing subthemes in more detail.

Work Product. Participants considered the output of the activities as an important aspect contributing to their productivity. We identified four factors constituting the work product: concrete output and progress, conceptual achievement, quality of the output, and quantity of the output.

Concrete output & progress and **conceptual achievement** refer to tangible and intangible forms of achievement from tasks, respectively. Producing concrete outputs—such as implementing a new feature, making a design artifact, or documenting a design idea—made participants perceive a task productive. It was also considered productive that they could resolve an issue or make a concrete progress from a meeting (e.g., making decisions on the agenda). In addition, conceptual achievement—such as gaining insights, coming up with ideas, and acquiring knowledge—contributed to productivity. In the exit interview, P9 remarked, "*When I learn new concepts I feel somewhat proud of it, although this feeling of making progress could be illusory ... I rated many such cases highly productive.*"

Both **quality** and **quantity** were important factors when assessing individuals' work product. Given that the output quality matters in knowledge work [18], we found many cases in which participants related the output quality to "how productive" they were in the task. In this vein, low output quality made them feel less productive and even stressful because it could hinder the progress or require additional task. Quantity of the output was usually manifested in modifier expressions: *many (decisions made)*, *much (inspiration)*, *largest (to-do items)*, or *various (ideas)*. Interestingly, a majority of the quantity-based reflection on work product was about the conceptual achievement rather than objective and quantifiable tasks.

Time Management. Recognizing *time* as a limited resource of life [54], participants reflected on time-related factors of their activities. We identified three time-related factors: efficiency & intensity, punctuality, and use of spare time.

Efficiency & intensity and **punctuality** both involve the elapsed time of the work, but their focus is different. For efficiency & intensity, participants focused on the perceived amount of work during a given period, or whether they completed a task faster than they expected or planned. A mental

Theme	Subtheme	Example Rationale Answers
Work product	**Concrete output & progress**	"*Presented future directions to the team and received feedback from them*" – *very productive* [P21]
	Conceptual achievement	"*Although it* [seminar] *was outside of my research area, it inspired me to reflect on my research directions.*" – *productive* [P11]
	Quality of the outcome	"*Because the quality of the design draft was so poor, it was stressful to go through the feedback I received*" – *neutral* [P24]
	Quantity of the outcome	"*I had a long conversation with my colleague for three hours. He gave me **much advice** on how to manage my career, how to bear a job, how to protect my work, and so on.*" – *productive* [P22]
Time management	**Efficiency & intensity**	"*Prepared for the class efficiently, pressured by a tight schedule*" – *very productive* [P11] "*Mainly small talks, in a business meeting.*" – *neutral* [P2]
	Punctuality	"*Answered all the emails in the inbox before the time to go home!*" – *very productive* [P7]
	Use of spare time	"*Read a book leveraging the time to commute.*" – *productive* [P4].
Worker's state	**Attention & distraction**	"*Highly focused in the morning; completed the presentation slide*" – *very productive* [P17]
	Emotional state	"*Grappled with the UI flow ... Ideas from two are better than one, and three are much better than two. I felt good!*" – *productive* [P22]
	Physical state	"*It dragged on as I was dozing*" – *neutral* [P16]
Attitude toward work	**Chores and mundane task**	"*It was just a Monday weekly meeting, rarely meaningful to me.*" – *neutral* [P21]
	Enjoyment of the task	"*Built and tested the app!! Although I was not in a good condition, I was completely focused on the work because it was enjoyable to produce highly concrete output.*" – *very productive* [P17]
	Significance of the task	"*Focused* [on the meeting] *because of my role* (scribe)" – *productive* [P23]
	Rewarding self-regulation	"*Even though I didn't want* [to go to the gym], *I did go!*" – *productive* [P20]
Impact and benefit	**Long-term career benefit**	"*Talked with my colleague about why I wanted to resign from the company, what was tough for me and what I couldn't resolve here ... I thought I should consider more alternatives including different types of startup companies*" – *very productive* [P22]
	Social and spiritual benefit	"*It is very productive to serve the community* [church] *I belong to*" – *very productive* [P13]
	Self-management & well-being	"[Drumming] *Not improved much 'cause I didn't practice hard ... beat is still unstable.*" – *neutral* [P16]
	Monetary rewards	"*Saved both time and budget, by buying an air ticket in advance*" – *productive* [P18]
Compound task	**Task switching by interruptions**	"*Found a critical issue in the app while improving the design of home screen -> Notified the problem to developers* [interrupting task] *-> Couldn't complete my original task*" – *neutral* [P16]
	Multitasking	"*Finished multiple tasks, including email follow-ups and phone calls, at once, which may normally take 3 hours long.*" – *very productive* [P9]
	Unexpected issues	"*The power strip had short-circuited, making me stop working and go home. Totally frustrated especially because I was highly productive until then. :(*" – *neutral* [P1]

Table 3: Six themes of productivity evaluation derived from the rationale field answers.

pressure imposed by a deadline or the next task in a queue sometimes led to high efficiency, whereas no urgency led some participants to be laid-back. The assessment of a meeting productivity frequently referred to efficiency & intensity: participants perceived a business meeting less productive when the conversation derailed. Low proficiency was also the cause of low efficiency.

For punctuality, participants focused primarily on whether they completed a task on time or met a deadline—either an external deadline (e.g., deadline to send a document) or self-imposed one (e.g., hoping to finish tasks before the closing hour). In some domains (e.g., counseling), punctuality was considered an important value. For example, P19 was sensitive to the punctuality of her counseling session (e.g., "*gave insights [to the client], finished on time*" – *very productive*). In the exit interview, she remarked a reason for this: "*Counseling is conducted under very strict rules so it's really important to be punctual ... everything we do is a promise between the client and myself, which gives insights to the client.*"

Use of spare time reflects participants' aspiration that they want to use or save their time wisely. Participants commonly used their commute time (e.g., on the bus, on the subway) to do personally meaningful tasks.

Worker's State. Personal states during or after the activity affected how participants perceive their performance or productivity. Participants captured three major states: attention and distraction, emotional state, and physical state.

Attention refers to the state in which participants were able to concentrate on their tasks, while **distraction** refers to diverting the attention by losing the ability to focus on their tasks. Participants felt they were productive when they could stay focused for a while because it affects the quality of output and work efficiency. In the entries, participants frequently mentioned that they could complete a task or produce an output as planned because they concentrated on the task. In contrast, participants felt less productive when distracted: they captured various distracting behaviors such as using social media or a smartphone.

Emotional and **physical** states also affected productivity. Participants recorded various psychological reactions to a task—such as feeling accomplished, satisfied, or depressed. For exercise and leisure activities, for example, participants perceived high productivity when they felt refreshed, relieved stress, or were pleased. Also, participants' physical condition was associated with other factors, such as attention and efficiency. The entries mentioning the physical state consistently indicated that a good physical condition yielded a high level of focus, and a poor physical condition yielded a low level of attention (e.g., dozing). Factors affecting the physical condition included sleep, fatigue, and sickness.

Attitude Toward Work. Participants' attitude toward a task influenced their perceived productivity—i.e., differences in receptiveness such as personal values, meaningfulness, significance, or willingness yielded different perception of productivity. We identified four salient types of such receptiveness: chores and mundane tasks, enjoyment, significance, and rewarding self-regulation.

Chores and mundane tasks, not pleasant but necessary routines, were what participants were usually unwilling to do, marking such activities to be the least productive (i.e., *neutral*). Participants seemed to distinguish the tasks involving their creative knowledge (e.g., design, development) from others (e.g., paperwork, data entry). When evaluating chores, participants rarely considered the quality, but how quickly they could handle the chores. On the other hand, **significant** tasks stimulated participants to be more focused. Dealing with a task with a potential to impact the work process or being in charge of making a decision were considered significant. Examples from the entries include making a big decision for the theme of design, gaining important information for decision making, and resolving a critical logic error in source code.

When participants **enjoyed** the task, they were immersed themselves and sometimes outperformed, feeling highly productive. In contrast, participants perceived a task less productive when they did not want to do it. Doing unenjoyable tasks, participants were likely to feel themselves distracted and inefficient.

Self-regulatory behaviors such as overcoming procrastination and partaking self-disciplinary activities were considered productive. For example, managing to go to a gym even when tired was considered to be productive regardless of the intensity of the exercise. Other examples included dealing with a postponed paperwork or housework.

Impact and Benefit. Participants valued the activities that have potential benefits on their careers, relationships, well-being, or finance. We identified four types of impact and benefits: long-term career benefit, social and spiritual benefit, self-management & well-being, and monetary rewards.

Long-term career benefit reflects participants' interests in personal development and their long-term career path. Participants captured activities that were expected to have positive effects on their career, such as developing a skill set or building a good professional reputation. At the time of the diary study, for example, P22 was concerning about a job transfer. She captured the productive activities of having conversations with colleagues or a family member that contributed to helping her make a decision (See example quotes in Table 3). In the exit interview, she explained the benefit of constructive conversation: "*Thinking a lot about my future and career, I felt I could benefit from talking with someone about it ... When I told my colleague that I was considering a transfer, he gave me helpful advice. It was interesting that I felt productive doing such things.*"

Social and spiritual benefit reflects participants' awareness of the relationships with others, and their personal faith. Participants considered their activities productive when the activities had a positive impact on their relationships with family or colleagues. In addition, two participants captured religious activities such as prayer, worship, and small group activities in church. Productivity of these activities were evaluated based on the *spiritual benefit* they delivered (e.g., concentrating on the prayer).

Benefits regarding wellness—**self-management & well-being** and **monetary rewards**—were connected to productivity. Participants aspired to enrich their well-being with activities such as *exercising*, *getting a haircut*, *having a hobby*, and *baking at home*. Although such activities were mostly considered productive by themselves, participants also considered the quality or intensity of activities for exercise or practice. Although relatively few cases were recorded, financial activities such as refinancing or buying an early-bird ticket financially benefited participants, and thus were perceived productive.

Compound Task. Sometimes, a few tasks were interleaved and performed in parallel. We identified three situations that involve compound tasks: task switching by interruptions, multitasking, and unexpected issues.

Task switching by interruption frequently occurred, making participants feel less productive. The interrupting tasks included urgent requests from a colleague, answering an urgent email or phone call, sporadic microtasks, and an

Category / Subcategory		Description	Entry Count	Example Task Names
Routine Task		Paperwork, writing and processing documents.	169 (20%) - 20Ps	Administration tasks, Handling documents
Learning		Information acquirement, learning, and knowledge gain.	164 (20%) - 20Ps	Attending Seminar, Search, Reading books, Taking an online course, Group speaking
Commu-nication	**Face-to-face meeting**	Communication in person, usually with colleagues.	182 (22%) - 17Ps	Project Meeting, Briefing, Counseling
	Emails	Dealing with e-mails	57 (7%) - 7Ps	Writing emails
	Conference Call	Communicating with people remotely.	20 (2%) - 5Ps	Customer comm., Phone call
Project	**Documenting & Conceptualizing Ideas**	Activities for planning and organizing ideas into a form of document.	118 (14%) - 12Ps	Planning service flows, Paper writing, Writing a user scenario
	Experiment & Development	Activities for implementation, experimentation, and problem solving through systemic processes.	68 (8%) - 5Ps	Programming, Conducting a molecular biological experiment, Data analysis
	Design	Producing design artifacts.	46 (6%) - 6Ps	Design-related, Logo design, Improving home screen
Personal	**Health**	Self-care for health and wellness including exercise and medical treatments.	52 (6%) - 10Ps	Corporate fitness center, swimming, yoga, receiving treatment
	Leisure	Activities which people perform during their free time to regenerate.	31 (4%) - 5Ps	Watching Netflix, Home brewing, Team retreat, [Hobby] drumming
	Social	Conversations, interactions, meals, and any other social activities with acquaintances or family.	17 (2%) - 6Ps	Personal conversation, With my family, Worship, Orchestra practice
	Living	Household activities, shopping, and finances.	6 (1%) - 4Ps	Housekeeping, Shopping for groceries
Scheduling & Environmental Setups		Coordinating schedules, reviewing past tasks, and maintenance activities for work-related facilities.	25 (3%) - 4Ps	Planning, Environmental setup for experiment

Table 4: Task categories with a brief description, entry count with the number of participants (Ps), and example task names. Note that a single entry can contain multiple tasks so there are overlaps in entry count.

unexpected roadblock during a task. In other cases, participants performed multiple tasks at once—i.e., **multitasking**. Unlike task switching, multitasking yielded mixed perceptions of productivity: simultaneous handling of mundane tasks was often perceived as incessant chores, whereas deliberate multitasking yielded a feeling of working intensively.

Unexpected issues, usually caused by the malfunction of facilities or work devices for the task, adversely affected the productivity. Participants perceived such cases less productive because they were unable to complete the task as planned or had to resolve that unexpected issues.

Task Types of Productive Activities

From the analysis of the 183 unique task names found in the entries' *tasks* field, we identified 13 prominent task categories (Table 4). Ten of them are grouped under three high-level categories—*communication*, *project*, and *personal*—based on their relevance. Some of the task categories are consistent with prior works regarding the capture of common activities of knowledge workers. For example, *routine tasks*, *emails*, *conference call*, *project*, and *personal* categories were also prevalent in Czerwinski and colleagues' work [12]. Reinhardt and colleagues [42] identifies a set of 12 actions in knowledge work, which roughly overlaps our categories in terms of learning, project, and communication. In this section, we highlight notable categories.

Learning. As information is an important capital for knowledge workers, learning activities covered both the work and non-work contexts. In workplace, participants took seminars or online courses mandatory for employee education. Sometimes they gathered references or case studies to inform the design of user interfaces. In the non-work context, participants read books or participated in a study group to learn or improve skills (e.g., learn how to speak English).

Communication. Communication was an essential activity of participants' work. Specifically, the *in-person* communication was very prevalent; Participants had frequent ad-hoc meetings for decision making, supervisor briefings, etc. In contrast to the prior works that considered *emails* as a prominent task of knowledge workers [12, 36], only seven participants treated handling emails as an explicit task. Instead, we found cases where participants considered emails as a part of a higher-level task, typically project-related; 12 diary entries described the email-related behaviors only in the *rationale* field. For example, P16 reported, "*App design renewal*" as a task and "*Finalized the design and sent it via email and messenger*" as a rationale.

Personal. Thirteen percentage of the diary entries (n = 106) contained personal activities submitted by 15 participants. Specifically, ten participants included health-related activities such as exercise and getting a medical treatment; five included their leisure activities such as hobbies; six included social activities such as hanging out with friends and participating in a religious group; and four included household-related activities such as a grocery shopping and cleaning the house.

5 DISCUSSION

Our study extends prior productivity research in two ways. First, we characterized what constitute productive activities. Second, we identified the productive activities beyond work-related tasks that people perceived to be important. Here, we discuss implications for designing technologies that can help individuals capture and improve their productivity.

Productivity as a Multifaceted Concept

In designing our diary study, we assumed that the target of productivity evaluation was task types and the time block. This decision was in accordance with existing productivity tools (e.g., [43]), where a person or a system assesses whether the time spent on a certain task was productive. However, our results drawn from people's productivity rationale showed that how people assess productivity is more complex than our assumption. Sometimes, a predisposition to a task—whether a task is significant or trivial—had a strong effect on people's productivity perceptions. In some occasions, people's emotional and physical states and their level of attention directly corresponded to the productivity. Other times, the result (i.e., work product, impact of the work) of the time spent was analogous to the level of productivity.

We note that many of the productivity attributes that we identified are largely missing from the current productivity tool design. For example, existing productivity tools rarely capture work product, even though this is one of the two defining factors of productivity (i.e., "output") according to the traditional term. Although we do not assert that all attributes we identified should be captured by the productivity monitoring tools, our results suggest that productivity be treated as a multifaceted concept rather than a homogeneous concept. As such, we should rethink how productivity tools should be designed to incorporate the level of sophistication.

Diverse Productive Activities in Work Contexts

As computing devices such as laptops, desktops, and mobile devices have been commonly used in knowledge work [24], prior productivity tracking tools and research studies have focused primarily on the work involving such devices. However, we observed many cases where work-related activities seemed to be performed without using computing devices. These activities included face-to-face meetings and offline learning activities (e.g., reading books and research papers). Also, prior studies show that people consciously do not use devices (e.g., lock them out of their phone when they need to focus), as well as move outside of the office environment (e.g., have walking meetings to avoid prolonged sitting and to increase in creative thinking [9]) to be productive.

The omnipresence of computing devices made the distinction between work and life fuzzy, which was also manifested in our study results. Although we did not report in depth, many of the work-related activities were performed outside the "typical" work hours of 9 a.m. to 6 p.m., which indicates that work can take place anytime and anywhere. When productivity tracking tools only account for the activities that involve computers or that take place in the traditional office setting—as in the case of many current productivity tools, we miss out important aspects of work. Thus, we should consider a broad range of tasks and work environments to be the focus of productivity.

Productive Activities in Personal Contexts

Although we did not restrict participants to capture only work-related activities for productivity evaluation, we had assumed that the majority of the tasks would be work-related, specifically regarding their primary job. However, we were surprised to find that a wide range of activities in personal contexts were perceived productive. The results implied that personal matters related to health, leisure, social, and household are as important as work-related ones and are subject to productivity evaluation.

During the study, one participant (P22) was thinking about switching jobs, which means that the activities that she did outside of her current job (e.g., updating resume and portfolio, having a conversation about job prospects) were considered as important as, or even more important than the activities for her current job. In general, activities that count toward participants' long-term career benefits were considered important and productive. For some, personal productivity may be achieved at the expense of organizational productivity; for others, organizational productivity has precedence over personal, or personally meaningful productivity. We see a growing number of workplace productivity monitoring tools (e.g., Desk Time [15], Time Doctor [49], Veriato [50]) designed to improve the overall organizational productivity. However, our investigation calls for a different kind of productivity tools that prioritize individual values and their long-term career, while having a symbiotic relationship with organizational productivity.

Factors Affecting Productivity

Rationales for productivity evaluation were highly related to one another, which was also the reason why we multi-coded. For example, *chores and mundane tasks* were frequently connected to *attention and distraction*, and the low attention was in turn connected to *efficiency and intensity*, leading to low perceived productivity. This connection is supported by other studies (e.g., *Bored* and partly *Rote* in [35], and *Chores* in [18]). Although confirming these observations in a quantitative way is beyond the scope of our investigation, it would be interesting to explore the relationship among some of the themes (e.g., between attitude toward work and efficiency). Furthermore, examining the causal relationship between productivity themes and productivity evaluation (e.g., relationship between the worker's state and the productivity) warrants future work.

Opportunities for Tracking Tool Customization

Although our study participants entered a large number of tasks (183 unique task names), individual participants engaged in only a handful of tasks (8.8 unique task names on average). In other words, there were large individual differences in participants' tasks, but each participant repeated a small set of tasks. This finding indicates the need and opportunity for customizing productivity trackers to fit an individual's context and preference.

In our study, manual tracking allowed participants to capture productive context and activities beyond the computerized environment (e.g., reading a printed research paper, having informal conversations). We, however, note that some tasks might be easy to track automatically, whereas others might require a person to manually register. For example, distracted behaviors involving computing devices such as visiting social media and activating or unlocking a smartphone can be easily captured automatically, but not manually. Moreover, they can also be classified as "unproductive" activities automatically, although such automatic classification is vulnerable to false-positive prediction.

Resolving this tension between the manual and automated productivity tracking is still a challenge for the design of comprehensive productivity monitoring tools. Recently, Choe and colleagues [7] introduced the notion of *Semi-Automated Tracking* in designing self-tracking tools by balancing both manual and automated capture methods. We envision that this semi-automated tracking approach is a promising direction for designing comprehensive and personalized productivity monitoring tools. In addition to the division of labor between manual and automated capture methods, the semi-automated tracking approach allows people to confirm or correct the measure of automated capture, which improves tracking tools' overall accuracy.

Our findings showed a broad range of evaluation metrics (e.g., importance, outcome, worker's state) and activity categories. Given the diversity of possible tracking items, having a tracker preparation phase for a week or so could help people identify personally meaningful tracking items and evaluation metrics. People then can leverage a flexible tracker creation platform such as OmniTrack [28] to create a custom tracker. Moreover, as people's tracking practice tend to change over time [28], it is important to allow them to refine the tracker design on the go.

Study Limitations

Although we aimed to recruit participants from diverse backgrounds (11 types of occupations), our study participants may not be representative of overall knowledge workers. For example, clinicians, writers, or journalists are a few examples who engage in the different nature of the work compared to our participants. Studying with a broader range of people would likely provide more diverse results (e.g., identifying new themes of productivity evaluation).

We also note that participants' cultural background might have affected our dataset: due to the long work hours in South Korea, our participants might have collected more entries or more work-related entries even though long work hours do not necessarily imply high productivity.

Our method could have oversampled less productive (i.e., neutral) activities and undersampled productive activities. However, prior studies have shown that people like to capture positive behaviors because it feels rewarding and good, whereas capturing negative behaviors can serve as negative reinforcement (e.g., [27]). In addition, 20.6% of productivity journal entries were captured at 9 p.m. or after, indicating "backlogging" or late work. We thus believe that our data capture protocol did not likely bias the dataset.

6 CONCLUSION

In this paper, we reported a diary study ($N = 24$) conducted to understand how knowledge workers conceptualize their personal productivity. Over the course of two weeks, we collected self-report data on activities that were perceived to be productive and the rationales for the assessment. From the diary and semi-structured interview data, we distilled rich contexts and various aspects affecting the perception of productivity, which are broad and highly personalized. As we rethink the design of productivity tracking tools, we envision leveraging the semi-automated tracking approach by combining both manual and automated ways to capture comprehensive and personally meaningful tasks. Our work contributes to the growing body of literature on personal informatics with a focus on personal productivity, providing implications for designing a comprehensive productivity tracking tools. We hope this study can help others working in the field gain insight regarding ways to better support tracking of personal productivity.

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