# PHYSICAL ACTIVITY IN THE CONTEXT OF EVERYDAY LIFE AND HOW WEARABLE ACTIVITY TRACKERS INCORPORATE INTO EVERYDAY LIFE OF OFFICE WORKERS

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**ABSTRACT**

Grace Shin: Physical Activity in the Context of Everyday Life and How Wearable Activity Trackers Incorporate into Everyday Life of Office Workers
(Under the direction of Dr. Bradley M. Hemminger)

Sitting in the office occupies so much of people's time that they often do not have time to exercise to stay in shape and maintain a healthy body weight. Because of the culture of hard work so deeply ingrained in Korea, Korean office workers have a sedentary lifestyle that they often do not have time to exercise.

Recently, wearable activity tracking device allows people to track and understand their daily physical activities. These devices monitor users' daily life and it could support of people who have a sedentary lifestyle by collecting their physical activity data. However, the device does not collect and consider users' contextual factors and environmental factors how those affects physical activity in daily life.

The objective of this dissertation is to discover how the context of everyday life affects physical activity steps in the use of wearable activity tracking device. This dissertation approach was triangulation mixed methods, using both quantitative and qualitative measures to identify a few everyday activities as a starting point and then tracking and analyzing those behaviors.

By using this triangulation mixed-method approach, including in-depth, semi-structured interviews and questionnaire assessments, supplemented with daily diary (as known as Ecological Momentary Assessment (EMA)) and activity log data, this dissertation aimed to concentrate on how the context of everyday life affects physical activity steps when using a wearable activity tracking device.

Furthermore, to examine the potential differences in the use and adoption of the devices, this study included two specific populations: 27 adopters and 66 abandoners.

To our knowledge, no studies have examined the utility of EMA methodologies by using wearable tracking device such as Fitbit to discover contextual and environmental factors that interaction with increasing physical activity among office workers. This study discovered integral contextual factors that could influence physical activity changes in the use of wearable devices in everyday life context. The findings presented in this dissertation add to our theoretical understanding of everyday life information practices. This also have practical implications for systems designers of wearable activity tracker who should consider users' environments, individual contextual factors, and information practices.

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# CHAPTER 1: INTRODUCTION

Sitting in the office occupies so much of people's time that they often do not have time to exercise to stay in shape and maintain a healthy body weight. Furthermore, prevention of work-related injuries, in particular among office workers and computer/video display terminal (VDT) users, is a major public health concern (Nieuwenhuijsen, 2004). There is evidence that office work can result in significant health problems (Bernard & BP, 1997).

Recently, wearable activity-tracking devices have allowed people to track and understand their daily physical activities. These devices monitor users' daily lives and could support people who have a sedentary lifestyle by collecting their physical activity data. However, the devices do not collect and consider users' contextual factors and environmental factors, as well as how they affect physical activity in daily life, which is important. In order to study the usage patterns of information technology and to see what factors affect increased physical activity incorporating the use of devices, it is necessary to investigate and understand users' environments and the contextual factors that come from them(Scherer, Craddock, & Mackeogh, 2011).

Ecological momentary assessment (EMA) is a novel method of data collection that provides reliable data collected about environmental and social contexts' influences on patterns of behavior within a participant's natural environment(Shiffman, Stone, & Hufford, 2008). To our knowledge, no studies have examined the utility of EMA methodologies by using wearable tracking devices such as Fitbit to discover contextual and environmental factors that interact with increasing physical activity among office workers. Therefore, by using the EMA method, this study will focus on contextual and environmental factors that could influence physical activity changes incorporating the use of wearable devices in an everyday life context.

Furthermore, the development of wearable activity trackers is presenting aspects of information behavior not covered well by previous research and most of the wearable activity tracker literature relates to the research areas of medicine (Schrager et al., 2017; Grindrod, 2014), human-computer interaction (Shih et al., 2015; Fritz et al., 2014; Gouveia, Karapanos, & Hassenzahl, 2015), sport science (Sasaki et al., 2015; Takacs et al., 2014; Dannecker et al., 2013), and behavioral science (Hayes & Van Camp, 2015; Sasaki et al., 2015). It's more difficult to find literature that approaches information science research. Wilson (2000) pointed out that the designers of information systems usually ask about how people are using the system rather than seek to determine what information people need and how information-seeking behavior relates to other behaviors which is more important to know. Therefore, it is important to understand what the information needs are for information-system users to achieve better information flow and to design better systems that lead to meaningful behavior changes.

Savolainen (1995) also stressed the contextual or situational factors in information-seeking behavior research: "In the refinement of the research framework one should devote closer attention not only to contextual or situational factors facilitating or impeding information seeking but also to availability and accessibility of information" (p. 290).

To reach to the aims of this research, this study examines the following research questions through a mixed-method approach, using office workers as the population and having them utilize wearable activity trackers (Fitbit).

**Research Question 1**: *What contextual factors (social and physical environments and personal characteristics [e.g., self-motivation]) interact with physical activity in everyday life incorporating the use of wearable activity trackers?* To explore Research Questions 1 with wearable activity tracker adopters (participants), EMA data, pre-interview survey data, Fitbit log data, and interview data are included to discover integral contextual factors in their daily lives in the office setting.

**Research Question 2:** *What information practices (information seeking, using, and sharing) can be identified in the context of the office workers who incorporate the use of wearable activity trackers in everyday life?* To explore Research Questions 2 with wearable activity tracker adopters (participants), EMA data, pre-interview survey data, and interview data are included to identify information practices of those who incorporate the use of wearable activity trackers in everyday life.

**Research Question 3**: *What are the differences between adopters and abandoners of wearable activity trackers, how are their motivations different, and what makes them keep using or abandon the device?* To conduct Research Question 3 with wearable activity tracker adopters and abandoners, interview and survey data are included to examine why users adopt or abandon activity trackers and to identify the possible cause of abandonment.

Therefore, this dissertation explores how the contextual factors and information practices of everyday life affect physical activity incorporating the use of wearable activity trackers. This study followed EMA protocols for collecting physical and social context data from office workers' physical and sedentary activities during their everyday lives.

# CHAPTER 2: LITERATURE REVIEW

## 2.1 Health and Physical Activity

### 2.1.1 Relation Between Sedentary Behavior and Physical Activity

Physical activity is "any bodily movement produced by skeletal muscles that requires energy expenditure" (WHO, 2017). Physical activity includes a wide range of human activities, from sport and exercise to hobbies or activities related to daily life (Miles, 2007). It has been emphasized that people who are not currently active can gain significant health benefits with a mild increase in physical activity and reduced sitting time (Hirvonen et al., 2012).

Evidence suggests that sedentary behavior may adversely affect health (Tremblay et al., 2010; Chen et al., 2009; Matthews et al., 2012). Reduced physical activity is related to several chronic diseases such as diabetes, various cancers, and obesity(Owen et al., 2010; Tudor-Locke, 2002). Research has shown that breaking up sedentary time with short-term physical activity has a positive impact on health by reducing sitting time (Healy et al., 2011).

Furthermore, several studies show that physical activity increases participation in social activities and functional health (Meisner et al., 2010; Stathi, McKenna, & Fox, 2010) and contributes positively to physical, mental and social well-being.

Physical activity is affected by many factors from the individual to the environmental, including demographics, health factors, time management skills, social characteristics and physical environment(Eyler, 2003). Therefore, it is important to understand both individual and environmental factors and how those factors affect the promotion of physical activity.

### 2.1.2 Traditional Measurements of Physical Activity

An accurate assessment of physical activity in everyday life is critical because of the close relationship between physical activity levels and health (Pitta et al., 2006). Traditional measurements of physical activity among people typically include self-reported questionnaires, diaries, and logs that require a recall process for respondents' activities (Harada et al., 2001; Tudor-Locke, 2002). However, sometimes people have difficulties with memory and cognition, making it difficult for them to recall their past activities accurately, especially over long periods of time (Harada et al., 2001; Baranowski, 1988). Furthermore, another limitation to self-reporting is it that questions could be interpreted differently by respondents (Wilcox et al., 2001). Not only can participants interpret research directions or questions differently, but they may also personally vary in their perception of activity levels and accuracy in recording data.

Although self-reporting approaches to measuring physical activity have been seen as an important way to understand context and patterns (Tudor-Locke et al., 2004), the utilization of objective measures of daily physical activity using electronic motion sensors (Westerterp, 1999) and pedometers (Tudor-Locke, 2002), has increased. Thus, physical activity data may be collected via such wearable activity monitors.

Pedometers are typically portable electronic devices worn on the waist that count the number of steps a person has taken by using a spring arm. Pedometers are useful for activities that researchers cannot observe directly, including daily activity assessment or measurement of the activities of several people at once (Van Camp & Hayes, 2012). However, due to insufficient memory storage space, someone other than the pedometer's user needs to record the number of steps taken by the end of each day.

Recently, several novel tracking devices using accelerometers have come on the market. These devices track steps and calculate activity levels using chip sensors (e.g., Fitbit, Samsung Gear Fit, Xiaomi Mi Band). Such fitness trackers, which are mainly worn on the wrist, offer a great supplement to self-reporting measures because the devices allow users to skip the recall process (Stahl & Insana, 2014), provide a direct and objective method of assessing physical activity, and reduce the systematic errors associated with the self-reporting measures (Hooker et al., 2011).

### 2.1.3 Interventions to Promote Physical Activity

Recognizing factors that affect people's physical activity may lead to the development of more effective interventions to promote physical activity (King, 2001). Possible effective behavior change strategies could include goal setting, providing rewards based on successful behavior, and self-monitoring of behavior (Michie et al., 2011). Previous evidence introduced a variety of effective interventions to promote behavior change in physical activity, including health education, exercise prescription, one-on one instruction, and social support (Ettinger et al., 1997).

King and his colleagues addressed the factors that may affect participation in physical activity. These included personal characteristics (e.g., demographic factors, health status, attitudes and beliefs toward physical activity) and psychological factors (King, Rejeski, & Buchner, 1998).
Each intervention strategy for physical activity is described below. These strategies are most effective when combined with each other (Craig et al., 2008).

#### 2.1.3.1 Health Education

Health education interventions not only change attitudes and beliefs about physical activity, but also work to promote physical activity by improving individual knowledge and skills (Kahn et al., 2002). Health education can aim at promoting and maintaining healthy behavior or preventing and treating diseases (Glanz, Rimer, & Viswanath, 2008). It can be delivered through interventions conducted in various contexts. Health education intervention is an important area to promote and maintain healthy behavior.

Studies have asserted that it is important to provide information about physical activity and to improve skills that increase individual confidence in physical activity (Trudeau et al., 1999; Bailey, 2006). A positive correlation between education and good health has been found in prior research. This is explained by improved knowledge of the relationship between health behavior and health outcomes, which leads to healthier behavior (Kenkel, 1991). The Internet has enabled utilization of voice-over-Internet software, video conference applications, and e-learning environments as tools for e-health education interventions to extend the reach of delivery (Glasgow, 2007). It enables combining the characteristics of face-to-face counseling with a mass communication approach to health education to increase the impact of interventions (Norman, 2008).

#### 2.1.3.2 Social Support

Social support interventions are activities designed to improve social support for physical activity through involvement from families, friends, organizations, and communities (Sherwood & Jeffery, 2000). Furthermore, online-based health interventions have adopted social support strategies including group chats, social network sites (SNSs), and discussion forums to increase physical activity (Atwood et al., 2018; N. Zhang et al., 2015).

Previous studies consistently insist that family and friends' social support positively affects physical activity (Carter et al., 2007; Eyler et al., 1999). Social support consists of three parts: informational support, which focuses on increasing knowledge about physical activity; emotional support, which provides an individual feeling of belonging to increase activity; and appraisal support, which provides encouragement for learning new skills relevant to an activity (Sherwood & Jeffery, 2000).

Interactivity can be considered a key feature in making the Internet a powerful health communication tool (Lustria, 2007). According to Lustria (2007), interactivity contributes to the persuasive capabilities of health communication and can affect comprehension and attitudes toward online social support forums. Targeting of information to a population subgroup whose members share the same characteristics, or tailoring of information to meet the needs of a specific individual, are methods used in health interventions to increase the impact of information and the effectiveness of interventions (Heidi Päivyt Karoliina Enwald & Huotari, 2010). For example, in an intervention aiming at smoking abstinence, highly tailored success stories and highly personalized messages were found to relate more to abstinence than outcome expectations, efficacy expectations, or the amount of exposure to intervention materials (Strecher et al., 2008; Norman, 2008). Individuals might also benefit from communicating with other people in the same situation or tackling the same kind of problems. Information about one's own experiences can be shared and discussed in peer groups (Cline & Haynes, 2001). Support from peers can help motivate someone to maintain positive health behavior (Bonniface & Green, 2007), and this can be utilized in an intervention.

**2.1.3.3. Self-Monitoring Intervention**

Already, many research studies have proved that self-monitoring intervention is an effective strategy in increasing physical activity (Williams & French, 2011; Gleeson-Kreig, 2006). Especially effective are self-monitoring strategies combined with goal setting and feedback strategies to increase the number of steps taken per day (Normand, 2008; VanWormer, 2004) .

Furthermore, self-monitoring has been used for different behavior change research, including smoking cessation (Brownell et al., 1986), weight control (Baker & Kirschenbaum, 1993), and diet (Peterson et al., 2014). In the behavioral treatment of obesity, self-monitoring is regarded as one of the most effective techniques (Romanczyk, 1974; Peterson et al., 2014) . These studies demonstrate the role of monitoring as an important factor in the treatment of obesity (Burke, Wang, & Sevick, 2011). Continuous monitoring of people's current behavior and health is one of the cornerstone measures that need to be taken (Meyer et al., 2014).

From the above range of health interventions to physical activities, my research mostly focused on self-monitoring intervention which employed a novel wearable activity tracking device.

## 2.2 Information Behavior and Health Behavior Change

### 2.2.1 Theoretical Frameworks for Information Behavior and Practices

There are various models and theories of information behavior and information practices (everyday information-seeking behavior). Several of these are described and elaborated upon in this section, focusing on how these models apply to information behaviors in everyday life contexts.

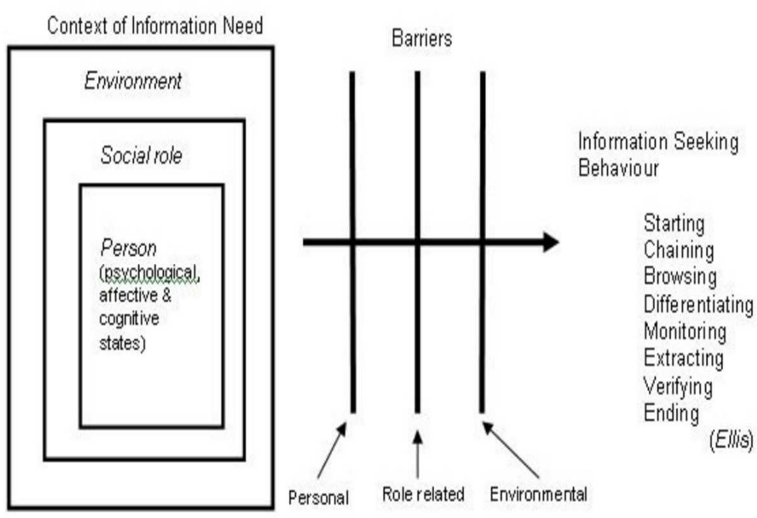
#### 2.2.1.1 Information Behavior

The frameworks that were chosen - Wilson's models of information behavior (Wilson, 1981a, 1997) , sense-making methodology (Dervin, 1992), and Kuhlthau's model of the information search process (1991) (Kuhlthau, 1991) - were selected because they either contain provisions for information needs or environmental, situational, and contextual factors in information behavior.

**Wilson's models of information behavior**

In the early 1980s, Wilson (1981) developed a descriptive process model of information seeking (Figure 2.1); it is commonly known as his first model of information seeking, since he subsequently developed more complex process models. The model begins with an information user with some type of information need. This need leads to three possible information behaviors, which are the need for information systems, the need for other sources of information, and the need for other people. Users may also express their needs to others in a process of requesting information that Wilson calls information exchange.

**Figure 2.1 Wilson's First Model (1981)**

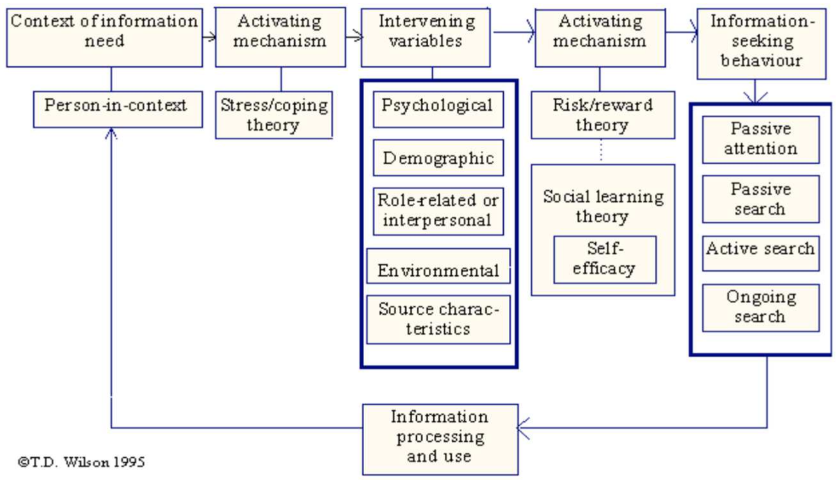



By including other people and other information in this model, Wilson emphasizes that people do not interact with information systems alone to meet information needs. Instead, users interact with others during seeking and use, and these interactions are reciprocal. However, the model has several limitations. First, it is a descriptive model and does not explain the causative factors between concepts (Wilson, 1997). This is a serious drawback. Since not all the concepts that appear in the model occur for all users, it needs to describe and enclose the connections between its concepts.

Although Wilson emphasizes that the point of this model is simply to "draw attention to the interrelationships among concepts used in the field [of information science]" (1981, p. 4), more work is needed to put concepts and their relationships in context.

He attempts to revise this in his model of information behavior, developed in 1995 (Figure 2.2). This model is much more complex and emphasizes contextual factors (Wilson, 1997). This model relies heavily on other theories, including stress and coping theories, reward theory, and social efficacy theory, to explain what Wilson calls an "activation mechanism" for information-seeking behavior.

**Figure 2.2 Wilson's Revised Model (1997)**




It also describes several intervention variables that are relevant to the individual depending on the information needs, the environment, and the characteristics of the sources that can be consulted. This model is too complicated to implement in practice. There are also several concepts absent from this model, such as information exchange. This indicates a conceptual shift away from others, focusing on the system as an information source (Niedźwiedzka, 2003).

**Dervin's sense-making approach**

Sense-making is an approach to understanding how people negotiate the uncertainties and discontinuities in life (Dervin, 1992). It considers information as "created at a specific moment in time-space by one or more humans" (Dervin, 1992, p. 63) — that is, information is composed either communally or internally as a way for people to make sense of life's discontinuities and uncertainties.

Sense-making cannot be thought of as simply a model of information behavior (Wilson, 1997); instead, it is often described as a theory with methodology (Case, 2012).

There are several key concepts in the sense-making approach: situations, gaps, outcomes, and bridges.The situation is simply the context of the information problem or need. When individuals face a situation, they my experience the existence of a gap: uncertainty, or discontinuity between the situation and their understanding or knowledge. To understand the situation and incidental gap, they undergo one or more communication activities, such as information seeking. These activities act as a bridge over the gap between situation and outcome.

The sense-making approach to information behavior has several strengths. It emphasizes the contextual nature of information needs, seeking, and use: there is no gap to bridge, no outcome that can be achieved, without first identifying a contextual situation that exists in both time and space. This aligned with my claim (assumptions) that to understand office workers' use of wearable activity tracking devices in more detail, we need to explore contextual factors and environmental factors in information behavior.

Furthermore, the sense-making approach emphasizes the role that the user, who is an individual with a specific gap to bridge, plays in information seeking, rather than focusing on the system or systems that users might employ to find information (Savolainen, 2006).

Therefore, sense-making is not considered as a solo activity: it is achieved only through communication (Brenda Dervin, Foreman-Wernet, & Lauterbach, 2003), and the approach highlights sharing activities between the sense-making individual and others as a central component of information behavior. Another strength of this approach is its broadness and flexibility; however, this could also be regarded as a weakness: because it is broad and flexible, it is difficult to apply in practice (Savolainen, 1993).

**Kuhlthau's model of the information search process**

Kuhlthau's information search process (ISP) model is described as "feelings, thoughts, and actions that follow as a person becomes aware of [that] gap" (Case, 2012, p. 145). This differs from other information behavioral models in that it is phenomenological in its approach, rather than cognitive (Wilson,1999).

In Information Search Process (ISP) , individuals initiate a search; this search arises from uncertainty and ambiguous thoughts about an information need. As people select sources, they become more optimistic. However, this optimism disappears quickly and is replaced by confusion, frustration, and doubt as they begin to explore further sources.

This occurs partially because the initial sources highlight aspects of the information need that were previously unknown to the individual. People may give up on their search at this point, based on how important their needs are. If they continue to search, they will eventually find clarity, along with the formulation of their true need. Finally, they present their sources in order to respond to their original information need, and this presentation may lead to an assessment of the success or failure of the search process (Kuhlthau, 1993). ISP is generally used in information-seeking behavior research with recognizable goals. Therefore, the applicability of ISP to gaps in knowledge that do not align with easily recognizable or measurable goals is limited.

**Table 2.1 Summary of Information Behavior Models**

| | Information Behavior Model | Limitation |
|---|---|---|
| Wilson's model of information behavior (1981) | · Model begins with an information user with an information need<br>· Need leads to three possible information behaviors: need for information systems, need for other information sources, or need for other people<br>· User does not interact solely with information systems | · Descriptive model<br>· Does not explain the causative factors between concepts<br>· Not all of the concepts that appear in the model will occur for every user |
| Wilson's model of information behavior (1995) | · More complex and emphasizes contextual factors<br>· Model relies on other theories: theory of stress and coping, reward theory, and social efficacy theory<br>· Several intervening variables: information need, environment, and the characteristics of sources | · Difficult to apply in practice because this model is so complex<br>· Several concepts are absent, notably information exchange<br>· Focuses on systems as information sources |
| Dervin's sense-making approach | · Approach to understanding how people negotiate the uncertainties and discontinuities of life<br>· Core concepts: situations, gaps, outcomes, and bridges<br>· Emphasizes the contextual nature of information needs, seeking, and use<br>· Emphasizes the role that the user plays in information seeking, rather than focusing on the system or systems<br>· Approach highlights sharing activities between the sense-making individual and others as a central component of information behavior | Both broad and flexible, it is difficult to apply in practice |
| Kuhlthau's model of the information search process (ISP) | · Described as "feelings, thoughts, and actions that follow as a person becomes aware of [that] gap" (Case, 2012, p. 145).<br>· Individuals initiate a search; this search arises from feelings of uncertainty and vague thoughts about an information need<br>· Uncertainty increases throughout the seeking process | The applicability of ISP to gaps in knowledge that do not align with easily recognizable or measurable goals is limited. |

### 2.1.2 Information Practice (Everyday-life Information Seeking (ELIS))

The concept of information practice, or more specifically everyday information practice, is relatively new. Information practices "may be understood as a set of socially and culturally established ways to identify, seek, use and share the information available in various sources such as television, newspapers, and the Internet" (Savolainen, 2008, p. 2-3).

The definition of information behavior that Wilson provided is "the totality of human behavior in relation to sources and channels, including both active and passive information seeking and information use" (Wilson, 2000, p.4). The concept of information-seeking behavior suggests that information seekers are "needy" individuals who must find information from a variety of sources. The concept of information behavior also assumes that information needs to lead to information seeking, especially the identification of various information sources.

Compared with information behavior, the key feature of information practice is "a more sociologically and contextually oriented line of research." (Savolainen, 2008, p. 120) The concept of information practice implies that information seeking and use processes are structured socially. In particular, information practice focuses on the role of the contextual elements of seeking, use, and sharing of information (Savolainen, 2008).

In general, information seeking may be seen as one of the necessary hallmarks of meaningful action, because without information seeking it is often impossible to interpret and make sense of one's daily world (Savolainen, 2008). Savolainen emphasized that 'information use' needed to be understood: "In particular, we lack qualitative research exploring how people make use of diverse information sources to further their everyday projects. However, such studies are vitally important; since information has no value in itself, information gains value when it is used…" (Savolainen, 2008, p.7)

The similarities between the models of information behavior and information practices are: 1) Both are used to identify the ways people typically deal with information. 2) Both researchers tend to be very fragmented and ambiguous, because they do not reflect how their studies relate to previously proposed definitions and are often content to propose their own definitions (Savolainen, 2008).

The difference between information behavior and information practices models is that information behavior is mainly triggered by need and motivation. Otherwise, information practice emphasizes the habitualization of activities that are influenced by social and cultural factors (Fransson, 2014).

**McKenzie (2008): A model of information practices in accounts of everyday-life information seeking**

Recognition of information needs actually represents the start of the information-seeking process (Shenton & Dixon 2003). Informal information needs arise every day. Much effort is needed when seeking information for non-school related projects and non-research related purposes (Agosto & Hughes-Hassell 2005).

Pamela McKenzie is one of the more active researchers in the field of information practice. She emphasizes the activities of individuals in a social context. McKenzie suggests different modes in the behavior of finding information in everyday life, such as 1) active seeking, 2) active scanning, 3) nondirected monitoring, and 4) proxy (McKenzie, 2003).

1. Active seeking: individuals looking for a specifically known source, conducting a systematic search, or asking planned questions, such as searching to find whether other people posted articles about activity tracking devices or health.

2. Active scanning: the task of identifying a particular source as either helpful or specific, such as following information about activity tracking devices or friends' Fitbit to see their daily steps.

3. Non-directed monitoring: a situation whereby an individual is exposed to information in an accidental or unlikely place, such as receiving information about exercise or activity tracking devices by chance when reading a friend's post on social media, watching TV, reading a magazine or surfing the Internet.

4. By proxy: a situation whereby an individual encounters a source through others, such as family members.

**Savolainen (2008): Model of Everyday Information Practices**

The concept of information practice is also discussed by Savolainen in his book, *Everyday Information Practices* (Savolainen, 2008). His model focuses on information practices accomplished in non-work contexts. Such contexts include leisure activities such as hobbies, participation in the activities of civil society, and activities related to problem-solving.

Savolainen suggests three modes of everyday information practices: 1) information seeking, 2) information use, and 3) information sharing. Under these three modes, six information practices in everyday life were identified: capturing information, reviewing information (Information Seeking), manipulating information, representing information, interpreting information (Information Use), and sharing information (Information Sharing).

The development of this model was primarily driven by the need to describe the role of social and cultural factors that influence the way people prefer and use information sources in everyday settings. Even if individuals choose and use different sources to solve problems or understand the daily world, source preferences and usage patterns are ultimately socially conditioned. Therefore, everyday-life information seeking attempts to combine social and psychological factors, even contextual factors.

McKenzie's information practices were used in my study for asking about activity tracking device users' information practices in daily life to understand their information use in everyday-life settings. Also, Savolainen's concept of social and contextual factors combined with information practices was used in my study. His argument—that careful attention should be given to the availability and accessibility of information as well as the contextual or situational factors that facilitate or hinder information seeking in elaboration of the research framework—was a great help for the general background of my research.

### 2.2.2 Theoretical Frameworks for Health Behavior Change

I reviewed several theories of health behavior change in order to employ their key concepts in my study. Among several health behavior change theories, the theories that were chosen — self-determination theory (Deci and Ryan 1980), social cognitive theory  (Bandura, 1986), and the transtheoretical model (Prochaska et al., 1997) — were selected because they appear useful for understanding adherence to physical activity and also emphasize environmental and social factors. I also describe here how these theories were actually used in several research studies focusing on physical activity changes using activity tracking technology.

#### 2.2.2.1 Social Cognitive Theory (SCT)

Albert Bandura's SCT explains how 1) Personal, 2) Environmental Influences, and 3) Behavior factors interact with each other to determine behavior (Bandura, 1986). His model emphasizes environmental and social influences that mean people learn not only through their own experiences, but also through the observation of people around them. In his theory, personal factors are described as self-efficacy, demographics, cognitive or affective factors, environmental influences (described as social environments), and behavior (described as characteristics of physical activity, such as intensity). Those three factors create a mutual causation relationship. For example, between personal factors and environment influences, personal self-efficacy, affect, thought, and belief are developed by social settings and environmental influences. People respond differently in their environments based on their demographic factors such as age, race, and gender  (Lerner, 1982).

There are several studies that adopt social aspects to access health behavior change (Marshall & Biddle, 2001; Riebe et al., 2005; Sarkin et al., 2001; Johnson et al., 2008; Webb et al., 2010).

For example, Toscos and colleagues (Toscos et al., 2006) developed the Chick Clique mobile application that motivates teenage girls to exercise by taking advantage of their social desire to stay in touch with their friends. They found that by providing positive feedback and supporting the relationship among friends, health information data sharing could be a powerful motivator to sustain physical activity.

In contrast to the above research findings, Klasnja and colleagues (Klasnja et al., 2009) discovered that when people were not confident about their physical activity data and they thought their physical activity data was not high, they were reluctant to share their data. In the study, the authors asserted that social support can be helpful, but devices should not depend on it alone to change behavior.

In relation to the social side, the problem raised in the long-term use of the wearable activity tracker was finding the right community or appropriate people with whom to share participants' data to motivate them (Fritz et al., 2014).

In Social Cognitive Theory, the social context and environmental context has substantial influence on behavior, and these assumptions were also proven in my research study. Applying this theory, wearable activity trackers could incorporate peer-to-peer feedback and encouragement. However, SCT does not affect all circumstances and environmental contexts in all users; instead, research should understand each person's environment factors, and then devices need to adopt personalized contexts when we design those kinds of activity tracking devices.

#### 2.2.2.2 Self-Determination Theory

Self-Determination Theory (SDT) is mainly used in understanding motivation and adherence to physical activity, and also other health-related behavior (Deci & Ryan 1985; Ryan & Deci 2000). According to SDT, there are two distinct types of motivation: intrinsic and extrinsic. Intrinsic motivation is described as internal drive to do behavior, such as a person with intrinsic motivation to do an activity, not because of extraneous reward or penalty but because of its inherent satisfaction (Ryan & Deci 2000).

SDT suggests three innate psychological needs — autonomy, competence, and relatedness — that spark intrinsic motivation. Their definitions are the following: autonomy is the feeling of having self-control over something; competence is perceived when a person understands his or her goal and the way to achieve it; and relatedness is when a person feels a sense of connectedness to others by sharing an activity with individuals, groups, or society (Ryan & Deci 2000).

There is some connection between wearable activity-tracking devices and the SDT theory's three innate psychological needs to improve physical activity. For autonomy, users can create activity goals based on steps, distance, or active minutes. Users can tailor goals to what will work best for their lifestyles and values. For competence, users are able to track activity progress and receive feedback on accomplishments that then support self-efficacy. For relatedness, users can connect with wearable activity tracking user friends (e.g., Fitbit Friend).

On the other hand, with extrinsic motivation, people tend to perform behaviors based on external rewards such as financial rewards or praise (Karageorghis, 1969). Extrinsic motivation drives a person to do an activity for "its instrumental value" rather than for its own sake (Ryan & Deci 2000). In relation to activity-tracking devices, for example, goal-related features and badges earned at different activity levels could be considered extrinsic motivators. Researchers have argued that activity-tracking devices create extrinsic motivation by reminding users of goals, helping them to reach a particular goal and congratulating them once it has been reached (Wendel, 2013). Several research studies that focused on goal-setting features provided activity tracking devices. For example, Fritz focused on the goal-setting aspect for encouraging physical activity, and the research discovered that customizable goal setting provided by the Fitbit system influenced the wearer's personal activity goals (Fritz et al., 2014). Thus, the goal should be to allow people to tailor their devices to different context and situations.

#### 2.2.2.3 Transtheoretical Model of Behavioral Change (TTM)

The Transtheoretical Model (TTM) developed by Prochaska is one of the most widely used in health behavior change theory (Prochaska, 1997). The TTM mainly consists of stages of change that define when people change and where people are in the process of change (Riebe et al., 2005).

There are six stages of change in the TTM sequence: 1) pre-contemplation, in which people do not have interest in change (no recognition of the need to change); 2) contemplation, in which individuals are beginning to think of changing; 3) preparation, in which individuals realize the benefits of making changes and thinking about how to change; 4) action, in which individuals are actively taking steps toward change; 5) maintenance, in which people are continuing commitment to sustaining behavior; and 6) termination, where the new behavior becomes sufficiently habitual and the risk of recurrence disappears.

People in the contemplation and preparation stages would be most receptive to an intervention since they have the highest potential to change. People in these stages are also the most likely to want and benefit from such a system. Movement through these stages does not occur linearly but in a cyclical manner, as many individuals relapse back to an earlier stage before ultimately progressing through all stages on their way to changing a particular behavior (Prochaska, 1997). I asked TTM-based questions to find out which participants in my study were at which stage, and which of those in the contemplation and preparation stages were active in using the device and were actually affected by the change. The three theories above have been, appropriately, the theoretical background of my research.

### 2.2.3 Information Behavior and Health Behavior Change

Readiness to change a behavior can affect how people deal with the information associated with that behavior (Bar-Ilan, Shalom, & Shoham, 2006). Providing information has been discovered to be a useful technique in physical activities (Van Achterberg et al., 2010). Information alone cannot guarantee healthy behavior, but sufficient information can lead to positive changes in people's health behavior (Lalazaryan & Zare-Farashbandi, 2014). When people lack knowledge or information about the health and benefits of a behavior, they may not be motivated to change their familiar, unhealthy habits.

To understand how information can affect people's behavior, Hirvonen and his colleagues carried out a study that augmented the Transition model of Behavioral Change (TTM) with the information behavior concepts. This model was used to observe patterns of avoidance or seeking of information about physical activity and the exercise levels of young men (Hirvonen et al., 2012). The results indicated that examining people's information behavior at the TTM stage of behavior change can support the design of a persuasive message to select the most appropriate customized strategies that help people improve their health (Enwald & Huotari, 2010; Enwald et al., 2012).

## 2.3 Wearable Activity Tracking Device

Recently, commercial activity trackers on the market (e.g., Fitbit, Samsung Gear Fit, Xiaomi) have made it easier for users to generate health-related data and allow them to track their daily activities such as step counts, calories burned, activity level, walking distance, and even sleep patterns. These devices can monitor users' physical activities, quantify their behavior and state of health, and automatically upload their data to the Internet.

My research focused on activity-tracking devices that help users modify their activity-based behaviors and require less effort to record user data in daily life. My research focused on the commercial activity tracking devices worn on body or clothing like Fitbit that people can easily obtain on the market. These are small devices; specifically, they are lightweight and suitable for wearing throughout the day and can last several days without the need for recharging (Guo et al., 2013).

I reviewed the previous literature that researched the use of wearable activity tracking device to find research gaps and what research methods were used.

I reviewed the literature that exhibited a clear focus on fitness tracking using wearable activity trackers. The following tables summarize the examples of previous literature that researched the use of wearable activity tracking devices. The categories were defined based on their research focus. Table 2.2 literature mostly focuses on technology and represents accuracy studies or more technical studies aimed at improving the functionality of devices. Table 2.3 mainly focuses on any behavior change that results from using the device, technology acceptance, and technology abandonment. Table 2.4 mainly focuses on a design-centric perspective including usability, and these studies were mostly published in the research area of human-computer interaction. Among those three big categories, I included a more specific research focus (e.g., "Comparison accuracy" in the Validation and Reliability table) in order to establish more concrete categories.

As I went through the research, I discovered that there is a research gap not only in the wearable activity tracker research field, but also in the different research methods used in the research. I discovered that the development of a wearable activity device presents aspects of information-seeking behavior not covered well in previous research. Regarding the research methods, the research methods used in the wearable activity tracker literature are various; for example, as shown in Table 2.2, experimental work mostly focuses on testing validity and reliability (also comparison accuracy), whereas field studies, interviews, and diaries examined the use of devices, usability in the wild, and contextual factors (shown in Table 2.4).

Based on the research gap in the literature on wearable activity tracker devices, my research is more focused on the information practices aspects of wearable activity tracker device use and also discovering contextual and environmental factors that affect the use of the device.

**Table 2.2 Example of Previous Literatures Focused on Validation and Reliability of Device**

| Research Focus | Author (year) | Sample Size | Sample Background | Data collection method | Analysis Method | Device usage for data collection | Devices |
|---|---|---|---|---|---|---|---|
| **Comparison Accuracy** | (Guo et al., 2013) | 3 | Not reported | Experiment | Quantitative analysis | Several weeks wore multiple devices at the same time | Fitbit, Nike +Fuelband, Pedometer, iPhone Moves |
| | (Case et al., 2015) | 14 | Healthy adults | Experiment | Quantitative analysis | Walk on a treadmill set | Fitbit, Nike +Fuelband, Jawbone Up, Pedometer Mobile apps |
| | (Fulk et al., 2014) | 50 | Chronic stroke and Traumatic Brain | Experiment | Intraclass correlation | Performed a 2-minute walk test | Fitbit, Nike + Fuelband |
| **Validity Reliability** | (Evenson, Goto, & Furberg, 2015) | 22 | N/A | Systematic review | Descriptive analysis | N/A | Fitbit, Jawbone Up |
| | (Kooiman et al., 2015) | 88 | University employees with an office job | Experiment (Laboratory)/ free-living conditions | Test-retest analysis | Walk on a treadmill set | Lumoback, Fitbit Nike +Fuelband, iPhone Moves, Pedometer, etc. |
| | (Dannecker et al., 2013) | 19 | Health young adult | Experiment | Mean standard error | Completed a four-hour stay in a room | Shoe-based physical monitoring device, Fitbit, DirectLife, Actigraph, etc. |
| **Effectiveness Feasibility** | (Naslund et al., 2015) | 10 | Serious Mental illness | Logged data/ Interview | Matrix analysis | 80 - 133 days | Fitbit Nike + Fuelband |

**Table 2.3 Example of Previous Literatures Focused on Technology and Behavior Change**

| Research Focus | Author (year) | Sample Size | Sample Background | Data collection method | Analysis Method | Device usage for data collection | Devices |
|---|---|---|---|---|---|---|---|
| **Technology & Health Behavior** | (Lazar et al., 2015) | 17 | Employees in technology company | Survey/Interview | Thematic analysis | Approximately 2 months | Lumoback, Fitbit, Nike Fuelband, Misfit Shine, etc. |
| | (Harrison et al., 2015) | 42 | Current and previous users | Longitudinal ethnographic study Survey/ Interview | Thematic analysis /Quantitative analysis | Vary. 2 weeks - 3 years | Fitbit, Jawbone Up, Misfit, iPhone Moves, Argus |
| | (Clawson et al., 2015) | 462 | Advertisements posts | Inductive and deductive method (Collected posts from Craigslist) | Inductive approach to analyzing 462 posts | N/A | Fitbit, Jawbone UP, Nike |
| | (Fritz et al., 2014) | 30 | Current device user | Interview | Open coding and closed coding | Who had been using such a device for at least three months | Fitbit, Nike FuelBand . |
| | (Wang et al., 2015) | 67 | Overweight and Obese | Randomized control | T-test | 6 weeks | Fitbit |
| **Technology Acceptance** | (Kim, 2014) | 44 | Female college students | Survey | Descriptive statistics | 90 consecutive days | Fitbit |
| | (Fausset et al., 2013) | 8 | Older adults | Experiment/Interview | Qualitative data analysis | 2 weeks | Striiv, Fitbit, Nike Fuelband, MyfitnessPal |

**Table 2.4 Example of Previous Literatures Focused on Design Centric Perspective**

| Research Focus | Author (year) | Sample Size | Sample Background | Data collection method | Analysis Method | Device usage for data collection | Devices |
|---|---|---|---|---|---|---|---|
| **Usability** | (Nelson, Verhagen, & Noordzij, 2016) | 210 | All individuals owned a smart wristband | Survey | Quantitative analysis | Majority of participants:1 year or less | Fitbit, Jawbone Up, etc. |
| | (Meyer et al., 2015) | 12 | Non-serious health problems | Exploratory study Interview, Diaries Qualitative field study | Quantitative analysis Qualitative analysis | 10 days | Fitbit, Nike +Fuelband, Jawbon Up, Pedometer |
| **Quantified Self** | (Choe et al., 2014) | 52 | 35% - Having health conditions: | Qualitative and quantitative method of 52 videos | Qualitative and quantitative coding analysis. | Average 25 months | Vary |
| **Device Use in Medical** | (Cook et al., 2013) | 128 | Postoperative cardiac surgical population | Quantitative (Collect steps from Fitbit device) | Descriptive analysis | 5-7 day | Fitbit |
| **Personal Informatics** | (Rooksby et al., 2014) | 22 | 4: lent activity tracker / 18: had used at least one tracker | Interview | Thematically analysis | Vary. Few months - More than a year | Vary |

# CHAPTER 3: METHODS

My research approach was triangulation mixed methods, using both quantitative and qualitative measures to identify a few everyday activities as a starting point and then tracking and analyzing those behaviors. A triangulation mixed-methods approach aims to collect data on a single topic and discover convergence across results. It employs both quantitative and qualitative methods to increase the validity of research by offsetting weaknesses (Greene, 2007; Mertens, 2009).

By using this triangulation mixed-method approach, including in-depth, semi-structured interviews and questionnaire assessments, supplemented with daily diary (as known as Ecological Momentary Assessment Data) and activity log data, this dissertation aimed to concentrate on how the context of everyday life affects physical activity steps when using an activity tracker. Furthermore, to examine the potential differences in the use and adoption of the devices, I included two specific populations: adopters and abandoners. A two-phase study was conducted to examine why users adopt or abandon the activity tracker and identify the possible cause of abandonment. In Phase 1, I conducted in-depth, semi-structured interviews with 27 participants. This was followed by collecting participants' diary entries and activity log data using activity trackers, which were used to examine ways the devices are incorporated into everyday life and reveal end user perspectives and practices of long-term use. In Phase 2, to better understand why some users abandon their devices, and to explore their experiences after discontinuing use, I carried out online questionnaire assessments and 5-minute exit interviews with 66 activity tracker abandoners who were reselling their devices online.

### 3.1 Study sample

Sitting in the office occupies so much of people's time that they often do not have time to exercise to stay in shape and maintain a healthy body weight. Furthermore, prevention of work-related injuries, in particular among office workers and computer/video display terminal (VDT) users, is a major public health concern (Nieuwenhuijsen, 2004). There is epidemiological evidence that office work can result in significant health problems (Bernard & BP, 1997).

Especially in Korea, as the nation moved into the era of modernization, hard work was highly valued by the society, and this trend is now reflecting itself among Korean companies as many employees usually work very long hours. It's common for a Korean worker not to be able to leave the office until their boss does and some bosses like to stay as late as possible. According to the Organization for Economic Co-operation and Development (OECD), South Korea has one of the highest average work hours in the world (OECD, 2016). South Korean tends to work 2,069 hours in 2016.

Because of the culture of hard work so deeply ingrained in Korea, people have a sedentary lifestyle which ultimately results in increased mortality (Booth & Chakravarthy, 2002). In 2015, JobKorea (www.jobkorea.co.kr), a portal service that provides information on how to get a job and lists available jobs and gives recruitment stats for employment, conducted a survey with 856 participants to ask about the status of exercise among employees. It revealed that about 8 out of 10 (85.6%) Korean office workers perceive that they lack exercise in daily life. The other 14.4% replied that they are doing enough exercise in their daily life. JobKorea also surveyed the reasons that Korean workers do not exercise, and the results are: 1) No time for exercise (35.70%); 2) lazy to workout (23.60%); 3) do not have enough money to exercise (financially-tight) (14.50%); 4) worry about tomorrow's work (14%); and 5) do not have friends who exercise together (11.10%).

Based on the Korean unique corporate culture, in order to discover how the context of everyday life affects physical activity steps in the use of activity tracking device, I choose Korean office workers as a study sample populations who have a sedentary lifestyle that they often do not have time to exercise.

The objective of this dissertation is to understand selected group's experience including adopters who were constantly using the wearable activity tracker and abandoners who had experienced using the device, but have stopped using it, I employed purposive sampling rather than random. Purposive sampling is designed to generate greater depth of information from sample and enhance understandings of selected group's of experience (Devers & Frankel, 2000). Random sampling would have produced stronger results. However, because it was difficult to recruit subjects for this study—particularly a good random sampling—I chose a purposive sample, where I recruited from a specific targeted work environment (where I was likely to get responses) that was representative of the population in which I was interested.

### 3.2 Recruitment

In this study, I employed two strategies for recruiting the adopters and abandoners populations. For Phase 1, as the aim of this stage was to understand how users of wearable activity trackers incorporate the devices into their everyday lives and explore their experiences in the use of the devices, I recruited adopters who are constantly using a wearable activity tracker. These device users participated in all data collection phases, including providing 5 days of Ecological Momentary Assessment (EMA) diary data, providing Fitbit log data, and taking 40 to 50-minute, semi-structured interviews. To more closely examine abandoners, Phase 2, consisted of a short online survey and 5-minute exit interview with participants who previously used the wearable activity tracker and stopped using the device for any reason. Similar to recruiting adopters, a random sample of abandoners would have been the strongest methodology. However, identifying and recruiting subjects for a random sampling is difficult. A good mechanism for identifying abandoners is to select those who are selling their devices. This has limitations in that the sample may be biased; perhaps certain types of people are more likely to resell devices than others are (based on personality type, financial status, interest in technology, etc.). This sample was chosen because it offered the best way in which to identify abandoners.

To recruit Korean office workers who have continuously used the wearable activity tracker, especially Fitbit (fitbit.com) device, I advertised the study on Fitbit Korea User Group, Naver Fitbit Online Korean Forum, Facebook Korea Fitbit User Group, and CLIEN Internet forum (https://www.clien.net). I choose to use Fitbit for this study because it is currently one of the leaders in the worldwide wearable market. Among a variety of wearable activity trackers on the market, approximately 26.3 million Fitbit devices were sold in the third quarter of 2017. The most popular wearable devices to date have been Fitbit (13.7%) and Xiaomi (13.7%) followed by the Apple Watch (10.3%) according to the International Data Corporation (IDC) (IDC, 2017). Furthermore, another reason that I choose to use the Fitbit device for my study is because Fitbit provides API (Application Program Interface), which allows developers to, with user permission, easily interact with Fitbit data and access participants' log data. There is also a mobile app, named Health Exporter for Fitbit to CSV, which allows users to export their Fitbit data into a CSV file.

The recruitment letter stated that we are looking for current users of Fitbit and full-time Korean office workers who are working more than 8 hours per day. The criteria for participating in this study were the following: 1) Who currently works at the office environment (full-time office worker); 2) at least 18 years of age, and 3) currently using Fitbit device for logging their physical activity records.

I joined each community listed in Table 3.1 to post the recruitment letter. Once participants contacted me by a text message, I sent them a more detailed description of the study, including what would happen in interview sessions, and that I would be asking for their consent to collect their Fitbit log data and 5-day EMA diary. Further, when participants inquired about participating in this study, I asked them several questions to determine whether or not they met the recruitment criteria. If they were selected for participation, I sent out a pre-study questionnaire to help me better understand their background, including their demographic data (Appendix A) . Next, based on each participant's availability, the EMA data were collected for a 5-day period. For compensation, participants were provided with a $20 (approximately 20,000 KRW) cash for their participation.

Of the participants, 24 were recruited from the online communities that I listed in Table 3.1, 1 participant was recruited by word of mouth, and 2 participants were recruited by snowball sampling (1 was a participant's wife, and 1 was participant's friend) of participants who were already involved in this study. I was able to obtain a sample of a suitable size for the Phase 1 study (N = 27).

A wide range of sample sizes was observed in the previous research when the researcher plans data collection for an in-depth interviews qualitative study. Most of the researchers agreed that a sufficient sample size is achieved when additional participants don't provide any additional insights, which is called saturation. However, how to define the exact numbers for such a study is still debated (Guest, Bunce, & Johnson, 2006). In the previous literatures, the most common sample sizes were 20 and 30, while 15 is the smallest sample (Bertaux, 1981, p.35).

To recruit individuals (abandoners) who have stopped using their wearable activity trackers, I contacted those who publicly posted advertisements about their wearable activity trackers, including Fitbit, Samsung Gear Fit, etc., in the online secondary sales market. In Korea, we have the largest online Flea Market; Naver Joonggonara (http://cafe.naver.com/joonggonara) that required membership for participation and currently the number of members are approximately 16,175,473 people (confirmed on Feb. 7th, 2018). For individuals who posted advertisements about their wearable activity trackers and included their contact phone number, I contacted them via text message describing the current study, explaining criteria for participating, and inviting them to join the project. The criteria for participants in the online survey were: 1) those who currently work in an office environment; 2) are at least 18 years of age; 3) previously used a wearable activity tracker but stopped using their device; and 4) are reselling their device. If they agreed to participate in this study, I sent an online survey questionnaire (Appendix D) and conducted a 5-minute exit interview by text message. Compared to recruiting adopters, it was more difficult recruiting abandoners who were selling their activity trackers via online secondary market. When I first explained the research project by contacting them directly with phone numbers posted on advertisements, there were quite a few who doubted my intentions.

There were approximately more than 200 text message contacts that I had from that initial study. The recruitment process for abandoners started from July 2017 to January 2018. I was able to obtain a sample of a suitable size for this phase 2 study (N=66).

**Table 3.1 Online Community that Recruitment Letter Posted for the Study**

| Site Name | Number of users | Membership Required for Participation |
|---|---|---|
| Fitbit Korea User Group (https://www.fitbit.com/group/228SRG) | 200 members | Yes |
| Naver Fitbit Online Korean Forum (http://cafe.naver.com/fitbituser/162) | 7646 members | Yes |
| Facebook Korea Fitbit User Group (https://www.facebook.com/groups/fitbitkorea/) | 438 members | Yes |
| CLIEN Internet forum (https://www.clien.net) | Not specified | Yes |

### 3.3 Data Collection

To examine how wearable activity trackers are incorporated into everyday lives of office workers and reveal perspectives and practices of long-term use of the devices, Phase 1 of this study consisted of four data collection phases for each participant. The order of the data collection for each participant was: 1) complete a pre-study questionnaire; 2) complete a 5-day diary (2 times per day, morning and evening); 3) allow study access to Fitbit log data; and 4) take a 40 to 50-minute interview.

**Table 3.2 Summary of Collected Data for Phase 1**

| Order | Collected Data | Data Collection Method | Duration |
|---|---|---|---|
| 1 | Pre-study questionnaire data | Provided online survey link by text message | Submitted once |
| 2 | Ecological Momentary Assessment (EMA) data | Provided online survey link by text message | 5 days (2 times per day, morning and evening) |
| 3 | Fitbit log data | Downloaded from Health Exporter for Fitbit to CSV mobile app | Submitted once |
| 4 | Qualitative interview data | One-on-one interviews or one-to-one phone interviews | 40-50 minutes |

### 3.3.1 Pre-Questionnaires

All participants were asked to complete a short pre-study questionnaire before starting the study. The questionnaire was provided with an online Google survey link by text message. All of the questions were written in Korean. In a pre-study questionnaire, participants were asked to fill out a demographic questions including socio demographic information (e.g., type of work, years of work experience), work-related stress question with 5 Likert scale (Giorgi et al., 2014), Stage of Change for Physical Activity question from the Transtheoretical Model (TTM) (Prochaska & Velicer, 1997), favorite types of physical activity from the Metabolic Equivalent Task (MET) table (Ainsworth et al., 1993), see Table 3.3, the revised version of Healthcare Technology Self-Efficacy (HTSE) (Rahman et al., 2016), and the revision of information behavior questions from Mackenzie everyday-life information practices model (McKenzie, 2003).

The participants' responses from the Stage for Change for Physical Activity questionnaire were used to assess their status of physical activity and their readiness to change their behavior in physical activity when they started using wearable activity trackers. Stage of change was measured using a validated instrument adapted from (Marcus et al., 1992).

The information behavior questions are modified from Mackenzie everyday-life information practices model (McKenzie, 2003). The subscales included were: (a) Information Needs, (b) Active Seeking, (c) Active Scanning, (d) Non-directed Monitoring, and (e) Receiving Information by Proxy; and (f) Sharing Information (g) Participating. These scales were comprised of statements describing the respondents' thoughts and behaviors (Appendix A) (Likert scale of 1 (never) to 5(regularly)).

**Table 3.3 Physical Activity Level Defined by MET (Metabolic Equivalents) Table (Ainsworth et al., 1993)**

| Activity Level | MET | Examples of Activity |
|---|---|---|
| Very Light | 1 - 1.5 METs | Standing, Reading, talking on telephone, Sitting in class, studying, note taking |
| Light | 2 METs | Walking at a slow pace (1-2 mi/hr), playing musical instrument, Light gardening, Light office work, light use of hand tools |
| Light Plus | 2.5 - 3 METs | Walking downstairs, Cooking, light housekeeping, shopping, Pushing stroller with child, walking dog, Walking at an average pace (2-2.5 mi/hr), slow dancing, Golf bowling, fishing |
| Moderately Vigorous | 3.5 - 4 METs | Walking at a brisk pace (1 mi every 20 min), Weight lifting, water aerobics, Walking on job, 3 mph (one mile every twenty minutes), in office |
| Moderately Vigorous Plus | 4.5 - 5 METs | Slow swimming, Most doubles tennis, Dancing (more rapid), Golf |
| Vigorous | 6 - 10 METs | Hiking, Jogging (1 mile every 12 min), Skiing, Tennis, Bicycling |

### 3.3.2 Introduction to Ecological Momentary Assessment (EMA)

Ecological Momentary Assessment (EMA) is a novel method of data collection that provides reliable data collects the environmental and social context on patterns of behavior within a participant's naturalistic environment (Shiffman, Stone, & Hufford, 2008). This data collection method is similar to a qualitative research diary method with paper and pencil (real-time self report assessment), which has been traditionally used to record everyday experiences of research subjects and questions about the credibility of the respondents' records (Bolger, Davis, & Rafaeli, 2003). Recently, however, the technique of collecting scientific data due to the technological development of electronic devices has made great progress in recent years. This EMA method minimizes recurrence bias by measuring the current experiences and behaviors of research subjects closely in real time in the natural environment of research subjects through electronic diaries to explore changes in the time and context of recorded experiences and behaviors.

The objectives of EMA methods may be the reliable assessment to collect the pattern of behavior and experience over time with minimal retrospective bias, or studying the impact of environmental factors (Shiffman, Stone, & Hufford, 2008). EMA employs electronic devices such as smartphones to prompt real-time self-report surveys throughout the day (Magallón-Neri et al., 2016; Paolillo et al., 2017).

A key concept that must be considered is that EMA assessments represent a sample of the participant’s experience. In traditional one-time, retrospective questionnaire assessment approaches, investigators assume they are capturing data about the person’s full range of experiences in one fell swoop. EMA approaches are applied when the attribute being assessed varies over time, and the assessments are conceptualized as sampling the person’s condition over time. EMA methods can substantially improve the reliability and validity of data, but when interpreting such data, it is important to still bear in mind the limits of self-report (Shiffman, Stone, & Hufford, 2008).

As this dissertation aims to explore how the context of everyday life affects physical activity steps in the use of wearable activity tracker, this study followed EMA protocols for collecting physical and social context data from office workers’ physical and sedentary activities during their everyday lives. For this study, after participants completed a pre-study questionnaire, I asked participants about their availability and when they would be ready to start begin collecting 5-day EMA diary data. Further, as my study objective was to explore how wearable activity trackers are incorporated into everyday lives of office workers, I collected data on the mornings and evenings of 5 consecutive work days (Monday through Friday). If participants were willing to start on Wednesday, the EMA diary data were collected on workdays through the following Tuesday. A total of 27 wearable activity tracker adopters participated in EMA monitoring during working days, with 2 surveys per day.

All EMA data was time-stamped in order to be aligned with Fitbit log data. The Fitbit device provided instantaneous log data including steps taken and kilocalories from each participant and it also measured moderate-to-vigorous physical activity (MVPA) and sedentary activity.

**1) Morning EMA Questionnaire**

For the morning questionnaires (Appendix B), the EMA survey link created through Google Forms was sent out via text message between 8:00 a.m. and 9:00 a.m. Participants were asked to complete a short question sequence on their smartphone (Figure 3.1) and submit it before 11:00 a.m. If a survey prompt was not answered, I sent a message again to remind participants to complete it; as such, the response rate could reach to almost 100%. All EMA surveys were written in Korean. The morning EMA questionnaire consisted of 14 questions and assessed self-reported information on participants' current activity, any physical activity in the morning, current mood, level of stress, plus information behavior related to their wearable activity trackers, and weather in the morning.

**Figure 3.1 Example of Screenshots for Morning EMA Questions Displayed on Smartphone**


## 2) Evening EMA Questionnaire

The evening questionnaires for the EMA survey (Appendix C) link were sent out via text message between 6:00 p.m. and 7:00 p.m., and participants were asked to complete a short question sequence on their smartphone and submit it before 9:00 p.m. Similar to the morning questionnaires, if a survey prompt was not submitted by 9:00 p.m., I sent a message to remind participants to complete it; as such, the response rate for the evening EMA questions could also potentially reach 100%. The evening EMA questionnaire consisted of 18 questions and assessed self-reported information on participants' current activity, physical activity that day, working hours and sedentary hours for the day, current mood, the day's stress level, plus information behavior related to their wearable activity trackers, and weather for the day.

### 3.3.3 Fitbit Log Data

Fitbit uses an accelerometer to sense user movement such as steps taken, floors climbed, and intensity of activity. The Fitbit API allows user log data to be conveniently shared with third-party applications. The “Health Exporter for Fitbit to CSV” mobile app is one of the third-party applications that export users’ Fitbit data into a CSV file that can be directly imported into Excel and Google Docs and the CSV file can be shared by message or email. The Fitbit log data from each participant was collected through “Health Exporter for Fitbit to CSV” mobile application (app). Participants were asked to download the “Health Exporter for Fitbit to CSV” mobile app and login with their Fitbit account to download their Fitbit log data. Next, participants shared their CSV file with me by email. Through this mobile app, I collected daily data of Resting Heart Rate (if device supported), Steps, Distance, Floors, Elevation, Minutes Sedentary, Minutes Light Active, Minutes Fairly Active, and Minutes Very Active. The Fitbit device calculates active minutes using metabolic equivalents (METs), which help measure the energy expenditure of various activities. User gets active minutes for activities after 10 minutes of continuous moderate to intense activity.

The Figure 3.2 is an example of the Fitbit log data from one of our participants. Analysis of Fitbit log data provided participants’ level of engagement (frequency of use) with the technology, changes of steps (also mean daily steps), sedentary minutes (mean daily time sedentary), lightly active minutes, fairly active minutes, and very active minutes during their periods of their use. Through usage frequency data, we could see if participants continued using the devices over time.

**Figure 3.2 Example of Fitbit log data downloaded using “Health Exporter for Fitbit to CSV” mobile app**

| | A | B | C | D | E | F | G | H | I | J |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Date | Resting Heart Rate | Steps | Distance | Floors | Elevation | Minutes Sedentary | Minutes Lightly Active | Minutes Fairly Active | Minutes Very Active |
| 2 | 14/11/2017 | 80 | 7117 | 5.11 | 3 | 9 | 1104 | 137 | 27 | 20 |
| 3 | 13/11/2017 | 81 | 6054 | 4.34677 | 4 | 12 | 892 | 126 | 6 | 8 |
| 4 | 11/11/17 | 80 | 10812 | 7.76301 | 6 | 18 | 1163 | 231 | 22 | 24 |
| 5 | 10/11/17 | 80 | 8739 | 6.30904 | 9 | 27 | 1242 | 160 | 21 | 17 |
| 6 | 9/11/17 | 79 | 9390 | 6.74202 | 5 | 15 | 1218 | 172 | 24 | 26 |
| 7 | 8/11/17 | 78 | 8575 | 6.15685 | 3 | 9 | 1246 | 152 | 19 | 23 |
| 8 | 7/11/17 | 78 | 8254 | 5.92637 | 8 | 24 | 926 | 148 | 11 | 29 |
| 9 | 6/11/17 | 78 | 8686 | 6.23654 | 6 | 18 | 1258 | 147 | 14 | 21 |
| 10 | 5/11/17 | 79 | 6171 | 4.46661 | 2 | 6 | 1276 | 135 | 2 | 27 |
| 11 | 4/11/17 | 79 | 8608 | 6.18054 | 19 | 57 | 1257 | 125 | 26 | 32 |
| 12 | 3/11/17 | 79 | 11837 | 8.56504 | 5 | 15 | 1194 | 182 | 22 | 42 |
| 13 | 2/11/17 | 79 | 9409 | 6.75566 | 4 | 12 | 1249 | 143 | 25 | 23 |
| 14 | 1/11/17 | 78 | 7052 | 5.09637 | 1 | 3 | 1281 | 112 | 13 | 34 |
| 15 | 31/10/2017 | 79 | 5738 | 4.11988 | 8 | 24 | 1303 | 111 | 13 | 13 |
| 16 | 30/10/2017 | 79 | 7726 | 5.54726 | 7 | 21 | 1254 | 162 | 6 | 18 |
| 17 | 29/10/2017 | 79 | 2177 | 1.56308 | 1 | 3 | 1384 | 39 | 12 | 5 |
| 18 | 28/10/2017 | 79 | 8418 | 6.04412 | 8 | 24 | 1270 | 151 | 11 | 8 |
| 19 | 27/10/2017 | 78 | 6676 | 4.79265 | 10 | 30 | 888 | 169 | 25 | 8 |
| 20 | 26/10/2017 | 77 | 5724 | 4.10983 | 3 | 9 | 897 | 159 | 5 | 3 |
| 21 | 25/10/2017 | 78 | 7394 | 5.30889 | 6 | 18 | 1275 | 132 | 14 | 19 |
| 22 | 24/10/2017 | 78 | 7652 | 5.49413 | 5 | 15 | 1253 | 174 | 3 | 10 |
| 23 | 23/10/2017 | 78 | 8386 | 6.02114 | 1 | 3 | 1252 | 167 | 9 | 12 |
| 24 | 20/10/2017 | 78 | 9363 | 6.72263 | 15 | 45 | 1206 | 148 | 47 | 39 |
| 25 | 19/10/2017 | 77 | 8936 | 6.41604 | 10 | 30 | 1230 | 152 | 22 | 36 |
| 26 | 18/10/2017 | 77 | 7227 | 5.18898 | 4 | 12 | 1268 | 172 | 0 | 0 |
| 27 | 17/10/2017 | 78 | 7419 | 5.32684 | 7 | 21 | 863 | 184 | 0 | 0 |
| 28 | 16/10/2017 | 78 | 6183 | 4.43939 | 5 | 15 | 1030 | 83 | 21 | 16 |
| 29 | 15/10/2017 | 78 | 5537 | 3.97556 | 4 | 12 | 1307 | 103 | 12 | 18 |
| 30 | 13/10/2017 | 78 | 7699 | 5.52788 | 4 | 12 | 1245 | 174 | 12 | 9 |
| 31 | 12/10/17 | 79 | 10375 | 7.48285 | 8 | 24 | 1198 | 212 | 10 | 20 |

### 3.3.4 Interviews

A total of 27 participants (N = 27) who constantly using the Fitbit device participated in-depth, semi-structured interviews. All of the interview participants contacted me directly after seeing the recruitment letter posted online. As the participants contacted me with their willingness to participate and share their experiences and all of the information, including EMA survey and log data, participants were actively involved in the research. The duration of interviews ranged from 45 to 60 minutes. Of the participants, 13 (N = 13) participated in face-to-face interviews at cafés near their jobs. Because of the diverse geographic distribution of the remaining 14 participants (N = 14) who live outside of Seoul, they were asked to participate in phone interviews. The interview was planned according to the participants' convenience between September 2017 and January 2018. All in-depth interviews were conducted in Korean, and the interviews were audio recorded and transcribed verbatim. I transcribed two-thirds of the interviews in Korean, and a professional transcriber did the one-third. After that, professional translator translated the interviews in to English after signing a confidentiality agreement. To protect participant confidentiality during interview and transcription processes, names and related identifiers were kept anonymous in all the transcripts. To encourage maximum responses from participants, I used more familiar language rather than scientific jargon (e.g., information behavior, stages of change in transtheoretical model, etc.). I used the following interview topic with questions about participants' behavior, experience, and preferences using wearable activity trackers.

Interview questions focused on the following (Appendix E for the interview guide):

- General Background (things not asked in the pre-questionnaire): work environment, opportunities to exercise at work, overall exercise frequency, general experience using the device
- Technology: technologies that participants have used in the past and are currently using regarding tracking physical activity
- Motivation: motivations for adopting wearable activity tracker
- Usability: the general ways participants used the device
- Informational Aspects: information behavior in the use of wearable activity tracker and type of information participants obtained from the device
- Behavior Change: potential changes in participants' behavior as a result of using the device

### 3.3.5 Survey

For Phase 2, to better understand why people abandon their devices and explore users' experiences after they stop using the devices, I conducted short online surveys with 66 abandoners (N = 66) who sold their wearable activity trackers in the online second sales market in Korea. The online survey consisted of 27, primarily closed-ended questions (see Appendix D for detailed survey questions). Only two questions were open-ended, and these were about how life had changed after abandonment and what device improvements they recommended. The closed-ended questions focused on: 1) sociodemographic and background information (e.g., gender, age, marital status, education level, working type, years of employment, average working hours per week, etc.); 2) physical activity habits and readiness to change physical activity when they first started using the device; 3) general ways the device was used in the past; 4) reasons for abandoning and selling their device; and 5) abandonment practices and users' experiences and lives after abandonment.

During a 5-minute exit interview, participants were asked about missing answers, and clarifications were given. Through this process, there were no missing values in the questionnaire, so it reached a 100% completion rate.

## 3.4 Data Analysis

My study consisted of various types of data: interview transcript (text data), EMA diary (numeric data), log data (numeric data), and online survey (numeric data). By collecting both qualitative and quantitative data, these different methods of obtaining information complement each other, increasing the validity of the data (Zohrabi 2013). Based on triangulation method design (Duffy 1987), my qualitative (interview transcripts) and quantitative data (EMA, log data, online survey) were analyzed separately and compared to and combined with the results of the quantitative and qualitative analysis. My results primarily consist of descriptive statistics for all collected data types, inference statistics for EMA of morning and evening data and Fitbit log data, and thematic analysis of interview data.

### 3.4.1. Quantitative Data Analysis

#### 3.4.1.1. Descriptive Statistics

Descriptive statistics were used for representing summary of demographic and background information, such as occupation, age, physical activity level, marital status, years of employment, etc. Furthermore, the descriptive statistics of EMA questions for 27 study participants and online survey questions for 66 abandoners are described in the Results section of Chapter 4. Descriptive statistics were analyzed using SPSS Statistics software (version 23; IBM Corporation, New York, NY, USA)

#### 3.4.1.2 Inferential Statistics

**Fitbit Log Data**

The Fitbit load data was employed to examine Korean office worker engagement with Fitbit (frequency of use the device) and their physical activity patterns.

**EMA Data and Fitbit Log Data**

An integration of reliable Fitbit logged data and self-report questionnaire (EMA) data on behaviors and emotions could provide new understandings into the interaction of physiological processes in everyday life (Blaauw et al., 2016). Linear Mixed Models (LMM) which are extensions of Linear Regression Models was used to assess the relationship between the EMA-reported data (e.g., kind of physical activity, today's working hours, stress, mood, transport regime, etc.) as the independent variables and Fitbit data (steps, intensity level of physical activity) as the dependent variables (see Table 3.4). The LMM was used to determine the interaction with the dependent variables and independent variables. The LMM is suitable for analyzing multilevel data such as collected as EMA method (West, 2009) it not only classifies the group but also take into account the various demographic factors such as age and gender, as well as allowing linear regression analysis with repeated measurements. LMM analysis provides correlation within individual on observations measured over various times is assumed (Liu, Rovine, & Molenaar, 2012). Therefore, this model is useful and available in analyzing repeated measurement data over times. Through this, we could discover potentially important predictors of the dependent variable.

To test significant differences between user predictions and the actual number of steps to see whether they are overestimated or underestimated, the Welch two-sample t-test was conducted.

All reported p values were considered statistically significant at an alpha level of < 0.05. Linear Mixed Model and Welch two-sample t-test was conducted using SPSS version 23 software.

**Table 3.4 Variables that Used in Linear Mixed Model Analysis (Included variable Names and variable types)**

| Variables | Name of Variables | Data Type |
|---|---|---|
| **Independent variables Morning:** EMA self-report questionnaire data | · Transportation regime | Categorical |
| | · Mood state in the morning | Categorical |
| | · Level of stress in the morning | Categorical |
| | · Number of checking Fitbit data in the morning | Categorical |
| | · Way for checking data (Fitbit device/mobile app/PC) | Categorical |
| | · Level of physical activity mainly done in the morning | Categorical |
| | · Physical activity performed on the way to work or at the office in the morning | Categorical |
| | · Feeling checked data: motivated | Categorical |
| **Independent variables Evening:** EMA self-report questionnaire data | · Whether left the office or not | Categorical |
| | · Mood state in the evening | Categorical |
| | · Today's working hours | Categorical |
| | · Today's sedentary time | Categorical |
| | · Level of stress | Categorical |
| | · Number of checked Fitbit data via Device | Categorical |
| | · Number of checked Fitbit data via App | Categorical |

| | | |
|---|---|---|
| | · Number of checked Fitbit data via PC/Web | Categorical |
| | · Level of physical activity in the evening | Categorical |
| | · All of the physical activities in the evening | Categorical |
| | · Compete with Fitbit friends | Categorical |
| **Dependent variables** | · Morning Steps Data (Reported by user after checking the step data on the Fitbit device during morning EMA survey) | Numerical (Continuous) |
| | · Evening Steps Data (Reported by user after checking the step data on the Fitbit device during evening EMA survey) | Numerical (Continuous) |
| | · Steps of the Day provided by Fitbit | Numerical (Continuous) |
| | · Activites-Minutes Lightly Active of the Day provided by Fitbit | Numerical (Continuous) |
| | · Activites-Minutes Fairly Active of the Day provided by Fitbit | Numerical (Continuous) |
| | · Activites-Minutes Very Active of the Day provided by Fitbit | Numerical (Continuous) |

### 3.4.2 Qualitative Data Analysis

27 interviews text data were analyzed using the qualitative content analysis that are used to analyze interview transcripts to reveal people's information-related behaviors and so to uncover patterns, themes, and categories important to a social reality (Zhang & Wildemuth; Wildemuth, 2016).

ATLAS.ti for Mac OS was employed to analyze the interview transcriptions data. ATLAS.ti, qualitative analysis tool, assists researchers in organizing and coding qualitative data in more efficient way. The unit of analysis was a theme related to participants' use and experience of wearable activity tracker (Glaser, Strauss, & Strutzel, 1968). I also used Microsoft Word documents in each of the codes to emphasize notable quotations.

### 3.4.3 Ensuring Validity of the Research

To enhance the validity of the data, results, and interpretation, the evidence asserted that researchers should attempt to collect data from multiple sources using different types of procedures, such as surveys, interviews, and observations (Zohrabi, 2013). To triangulate the data, I employed a variety of data collection methods using a variety of sources and techniques, including online surveys, in-depth, semi structured interviews, diaries, and collecting log data from activity trackers. Each method presented research limitations. For example, in-depth, semi-structured interviews may include unintentional memory errors and recall biases (Ebrahim & Bowling, 2005). Additionally, my research was usually not completed in the environment in which the behaviors occurred. Therefore, by using different types of complementary procedures for collecting, comparing, and augmenting the validity of the data and their interpretation, researchers could provide better understanding of individual everyday lives unfolding over time (Onwuegbuzie & Collins, 2007).

Furthermore, Merriam (1998) suggested a methods for ensuring validity of qualitative research data: member checks. Lincoln & Guba (1985) stated that the method of member checks is "the most crucial technique for establishing credibility" (p. 314). For member checks to be confirmed and validated, the results and interpretations of the interviews are given to the interviewees (participants) to confirm the reliability of information and narrative of what they stated during the interviews. During the data analysis, I conducted member checks with all 27 participants via text message to confirm the contents of their interview statements and to ask for more details about what they said during their interviews.

# CHAPTER 4: RESULTS

By including different data types, I was able to give a richer and more complex demonstration of how the context of everyday life affects physical activity steps through the use of wearable devices than would have otherwise been possible with one data type. This chapter is comprised of three sections. Section 4.1 includes descriptive statistics of the Phase 1 study (for device adopters) that includes demographics and responses to work-related questions, physical-activity-related questions, wearable-activity-tracker-related questions, and information-behavior-related questions of adopters. I also provided a summary of Fitbit log data provided by adopters through a data exporter mobile application (4.1.4). Section 4.2 consists of results of Ecological Momentary Assessment (EMA) data, not only including descriptive statistical results of EMA data but also inferential statistical analysis of EMA data. Section 4.3 consists of descriptive statistics and 5-min exit interview data from the Phase 2 study of device abandoners. This section includes descriptive statistics of demographics, responses to physical-activity-related questions, wearable-activity-tracker-related questions, motivation to start using a wearable activity tracker, and reasons for abandonment.

## 4.1 Phase 1: Demographics and Characteristics of Adopters

This section describes the demographics (see Table 4.1) of 27 research participants (eight females and nineteen males) using Fitbit on a continuous basis. As mentioned earlier in the Research Methods chapter, 24 of the participants were recruited from online communities, one participant was recruited by word of mouth, and two participants were recruited by snowball sampling.

### 4.1.1 Demographic and Job Descriptions

***Demographic Descriptions (see Table 4.1).*** The age of the sample population ranged from 19 to 44, with the highest number of participants ranging from 30 to 34 years of age (n=9), and fourteen participants (51.9%) were married. All participants were highly educated, and most had a bachelor's degree (n=21) or a master's degree (n=6). This result reflects the fact that if people desire to work as office workers in Korea, they must have at least a bachelor's degree to be hired.

**Table 4.1 Demographics of Phase 1 Interviews and Diaries Study Participants (n=27)**

| Participant Demographics | Frequency | Percentage Frequency (%) |
|---|---|---|
| *Gender* | | |
| Male | 19 | 29.6 |
| Female | 8 | 70.4 |
| *Age* | | |
| 19 - 24 | 1 | 3.70 |
| 25 - 29 | 4 | 14.81 |
| 30 - 34 | 9 | 33.33 |
| 35 - 39 | 7 | 25.92 |
| 40 - 44 | 6 | 22.22 |
| 45 - 49 | 0 | 0 |
| 50 and over | 0 | 0 |
| *Marital Status* | | |
| Single | 13 | 48.1 |
| Married | 14 | 51.9 |
| *Education* | | |
| High school | 0 | 0 |
| Bachelor's degree | 21 | 77.8 |
| Master's degree | 6 | 22.2 |
| Doctorate | 0 | 0 |

***Job Description (see Table 4.2).*** All participants described themselves as office workers. Among them, fourteen (51.9%) participants were working at an Information Technology (IT) company. It seemed that over half of participants (n=14) came from IT companies that were technology oriented, and they were more curious about activity trackers. Six (22.2 %) participants reported that they were working in the education field. One participant was working at a finance company, and another was working in medicine. Other fields of work that participants reported included a law firm , a trading company, a construction company, and a science research institution. Thirteen participants were located in Seoul (48.1%), which is the capital of South Korea, and others (51.9%) were located in different cities, including Daegu, Gwangju, Daejeon, Ulsan, and Daejeon, which are located about 1 hour or more by car from Seoul. Ten participants (37.03%) had worked within a range of 1 to 4 years, and eight (29.62%) participants reported they had worked within a range of 5 to 9 years. The majority (n=25) reported that they typically work more than 40 hours per week. Over half (n=17) reported they usually get stressed at work.

**Table 4.2 Descriptive Statistics for Work-related Questions of Adopters (n=27)**

| Participant Demographics | Frequency | Percentage Frequency (%) |
|---|---|---|
| *Field of Work* | | |
| Finance | 1 | 3.7 |
| Information Technology | 14 | 51.9 |
| Medicine | 1 | 3.7 |
| Education | 6 | 22.2 |
| Other | 5 | 18.5 |
| *Workplace* | | |
| Seoul | 13 | 48.1 |
| Other | 14 | 51.9 |
| *Years of Employment* | | |
| Less than 1 year | 3 | 11.11 |
| 1 - 4 | 10 | 37.03 |
| 5 - 9 | 8 | 29.62 |
| 10 - 14 | 3 | 11.11 |
| 15 and over | 3 | 11.11 |
| *Working Hours Per Week* | | |
| Less than 40 hours | 2 | 7.4 |
| 40 - 44 | 20 | 74.1 |
| 45 - 49 | 4 | 14.8 |
| 50 - 54 | 1 | 3.7 |
| 55 and more | 0 | 0 |
| *Stress Level at Work* * | | |
| Not at all (1) | 0 | 0 |
| Least stressed (2) | 10 | 37.03 |
| Somewhat stressed (3) | 7 | 25.92 |
| Extremely stressed (4) | 9 | 33.33 |
| Most stressed (5) | 1 | 3.7 |

*Likert Scale (1: Not at all, 5: Most stressed)

### 4.1.2 Physical Activity Related Descriptions (see Table 4.3)

Participants were asked to report their physical activity (PA) status, including the amount of exercise per day, favorite type of PA level, the PA they typically performed while working (opportunity for PA), and the readiness to change their PA when they first started using a wearable activity tracker. The two physical activity-related questions were based on an physical activity level question and a readiness to change physical activity question from previous studies. The question about favorite types of physical activities levels was defined based on the Metabolic Equivalent Task (MET) table (see Table 3.3) (Ainsworth et al., 1993). Additionally, the question about readiness to change physical activity was adopted from the TTM stage of change using a validated instrument adapted from Marcus et al., (1992). Finally, the questions about the amount of exercise per day and the physical activity participants typically performed while working (opportunity for physical activity) were constructed to explore their daily physical activity pattern.

Most of participants were active, in that 22 (81.4%) of the participants exercised at least 30 minutes per day. Specifically, 8 participants (29.6%) exercised 30 mins to 60 minutes; 13 (48.1%) 60-120 minutes; 1 (3.7%) 120-180 minutes) (see Table 4.3).

Seven participants (25.9%) participants reported that their favorite levels of PA are Light (e.g., walking at a slow pace) and two participants (7.4%) reported that their favorite levels of PA are Very Light (e.g., reading, standing, sitting in office). Five participants (18.5%) reported that their favorites levels of PA are Moderately Vigorous (e.g., weight lifting, aerobics) and seven participants (25.9%) reported that their favorite levels of PA are Moderately Vigorous Plus (e.g., hiking, skiing). Their levels of PA changed little by little according to the day during the 5-day EMA (Ecological Momentary Assessment) questionnaire period. The participants performed PA to increase their PA level (step counts) while they worked, as follows (i.e., the top three include): 1) Take a walk within the company (34.9%); 2) walk to the office (25.4%); and 3) use the stairs instead of the elevator (23.8%). As I mentioned above, I also asked about their readiness to change their PA when they first started using the device, based on the five stages of change from the TTM theory, to understand their different mindsets toward changing their exercise behavior(Prochaska and DiClemente 1983; Nigg et al. 2011). No one described him or herself as being on the “pre-contemplation,” stage which represents, “I am not physically active, and I don’t plan on doing any PA in the near future." Six participants (n=6) described themselves to be on the contemplation stage; six (n=6) were on the preparation stage; eight (n=8) were on the action stage; and seven (n=7) were on the maintenance stage. All the participants at least had the mindset and willingness to change their PA when first starting to use the device.

**Table 4.3 Descriptive Statistics for Physical Activity Questions of Adopters (n=27)**

| Physical Activity Related Questions | Frequency | Percentage Frequency (%) |
|---|---|---|
| *Physical Activity (walking, running, working out) each Day* | | |
| Less than 15 minutes | 1 | 3.7 |
| 15 mins - Less than 30 minutes | 4 | 14.8 |
| 30 mins - Less than 1 hour | 8 | 29.6 |
| 1 hour- Less than 2 hours | 13 | 48.1 |
| 2 hours - Less than 3 hours | 1 | 3.7 |
| More than 3 hours | 0 | 0 |
| *Favorite Types of Physical Activity Level* | | |
| Very Light | 2 | 7.4 |
| Light | 7 | 25.9 |
| Light Plus | 4 | 14.8 |
| Moderately Vigorous | 5 | 18.5 |
| Moderately Vigorous Plus | 7 | 25.9 |
| Vigorous | 2 | 7.4 |
| *Opportunity for Physical Activity at/through Work* * | | |
| Walking to the office when commuting | 16 | 25.4 |
| Go to the gym to workout | 7 | 11.1 |
| Use stairs instead of elevators | 15 | 23.8 |
| Participate in exercise programs at work | 1 | 1.6 |
| Take a walk in the company | 22 | 34.9 |
| Other (e.g., riding bicycle) | 2 | 3.2 |
| *Readiness to change physical activity* | | |
| Pre-contemplation | 0 | 0 |
| Contemplation | 6 | 22.2 |
| Preparation | 6 | 22.2 |
| Action | 8 | 29.6 |
| Maintenance | 7 | 25.9 |

* Multiple selections possible

### 4.1.3 Wearable Activity Tracker-Related Descriptions *(see Table 4.4)*.

Over half (n=15) of participants reported using their wearable activity tracker more than 1 year. Actually, there was a slight difference between the device usage period that the participants self-reported during the pre-questionnaire and the days of using the device that were shown in the Fitbit data. Analysis of the Fitbit log data, including the mean steps and level of engagement with the device, will be covered in more detail in chapter 4.1.4 below. Based on the modified Health Technology Self-Efficacy (HTSE) questionnaire (Rahman et al., 2016), the results indicated that most of the participants (n=23, 85.2%) described that they had full confidence in using wearable devices. The results implied that my participants were quite technology oriented and that they were more familiar with using activity trackers. Steps (40%) data were the most interesting data that people checked daily, followed by sleep (27.7%), distance (12.3%), heart rate (10.8%), and calories (9.2%). Twelve participants (n=12) on average had a positive view regarding the number of steps they had taken each day (on average, they felt “very satisfied” that they walked enough), while thirteen participants (n=13) had a negative view of the number of steps they had taken each day, in that they usually felt regretful for not reaching the desired target when they checked their data.

**Table 4.4 Descriptive Statistics for Wearable Activity Tracker Questions of Adopters(n=27)**

| Wearable Activity Tracker Related Questions | Frequency | Percentage Frequency (%) |
|---|---|---|
| *Data type that accessed mainly ** | | |
| Steps | 26 | 40.0 |
| Heart rate | 7 | 10.8 |
| Distance | 8 | 12.3 |
| Calories | 6 | 9.2 |
| Sleep | 18 | 27.7 |
| *Satisfaction of steps data on average* | | |
| Very Satisfied | 12 | 44.4 |
| Regretful for not reaching the desired target | 13 | 48.1 |
| Passable | 2 | 7.4 |
| *Health Wearable Technology Self-Efficacy* | | |
| Easy to use the device | 23 | 85.2 |
| Not easy, but can use it in an appropriate manner | 4 | 14.8 |
| Not comfortable | 0 | 0 |
| Worry to break the device when in use | 0 | 0 |
| *Device Usage period* | | |
| 1 month - less than 3 months | 8 | 29.6 |
| 3 months - less than 1 year | 4 | 14.8 |
| 1 year - less than 2 years | 6 | 22.2 |
| 2 years and over | 9 | 33.3 |

* Multiple selections possible

### 4.1.4 Summary of Participants' Fitbit Log Data

The raw data generated by Fitbit collected the mean of steps and level of engagement with the device. The registered mean steps of all participants (n=27) was 9376 (low: 5467; high: 16997). These reliable Fitbit data provided the exact days of using the device compared to self-report responses from the pre-questionnaire that asked participants to provide the device usage period. The days of using the device varied, ranging from 31 to 1002 days (almost 3 years). The findings indicate that most of the research participants showed a high average level of usage: 77.30 to 100%. Surprisingly, 21 participants showed a 100% level of engagement with the wearable device. Based on the device usage period from the reliable data, eight participants (the same number of participants in the self-report questionnaire) reported that their device usage included *1 month - less than 3 months*, four participants (the same number of participants in the self-report questionnaire) reported *3 months - less than 1 year*, eleven participants (compared to the six participants who reported in the self-report questionnaire) reported *1 year - less than 2 years,* and four participants (compared to the nine participants who reported in the self-report questionnaire) reported *2 years and over*.

**Table 4.5 Summary of Participants' Fitbit Log Data information (*** p-value: < 2e-16)**

| PID | Gender | Mean Registered Steps (± SD) | Days Device Used | Days Device Unused | Device Usage (%) |
|---|---|---|---|---|---|
| **1** | Male | 11231 *** (± 224) | 425 | 4 | 99.06% |
| **2** | Male | 12794 *** (± 280) | 755 | 0 | 100% |
| **3** | Female | 8539 ** (± 1038) | 31 | 0 | 100% |
| **4** | Male | 8492 *(± 1182) | 46 | 0 | 100% |
| **5** | Female | 7534 *** (± 649) | 58 | 0 | 100% |
| **6** | Female | 7736*** (± 347) | 306 | 0 | 100% |
| **7** | Male | 7736 *** (± 303) | 514 | 0 | 100% |
| **8** | Male | 6772*** (± 700) | 49 | 0 | 100% |
| **9** | Female | 11264 *** (± 279) | 768 | 3 | 99.61% |
| **10** | Male | 16317 *** (± 626) | 63 | 0 | 100% |
| **11** | Male | 6909 *** (± 315) | 415 | 23 | 94.74% |
| **12** | Female | 16997 *** (± 626) | 63 | 0 | 100% |
| **13** | Male | 9117 *** (± 269) | 971 | 0 | 100% |
| **14** | Male | 14328 *** (± 359) | 274 | 0 | 100% |
| **15** | Male | 8081 *** (± 292) | 598 | 13 | 97.87% |
| **16** | Male | 9411 *** (± 450) | 141 | 0 | 100% |
| **17** | Male | 10584 * (± 322) | 401 | 0 | 100% |
| **18** | Female | 11958 * (± 305) | 503 | 0 | 100% |
| **19** | Male | 8996** (± 682) | 52 | 0 | 100% |
| **20** | Male | 7276*** (± 356) | 218 | 64 | 77.30% |
| **21** | Male | 7591 *** (± 311) | 463 | 1 | 99.78% |
| **22** | Female | 5819 *** (± 319) | 416 | 0 | 100% |
| **23** | Male | 9869* (± 598) | 70 | 0 | 100% |
| **24** | Male | 5467*** (± 283) | 714 | 0 | 100% |
| **25** | Male | 11356*** (± 268) | 1002 | 0 | 100% |
| **26** | Female | 8223*** (± 307) | 485 | 0 | 100% |
| **27** | Female | 7230*** (± 317) | 426 | 0 | 100% |

### 4.1.5. Information Behavior and Information Practices Descriptions

Table 4.6 shows a summary of responses for participants' statements that describe PA and wearable activity tracker-related information behavior. This questionnaire was modified from Mackenzie's everyday-life information practices model(McKenzie, 2003). Most participants reported that they were *often* (n=12, 44.4%) and *regularly* (n=11, 40.7%) interested in information concerning PA and wearable activity trackers (Fitbit) or felt like they should know more about it. Concerning who searched (through information practices of active seeking) to find whether other people posted articles about wearable activity trackers and to find whether there was a discussion group about wearable activity trackers, of the total participants, nine (33.3%) reported *often*, seven participants (25.9%) reported *sometimes*, and four participants (14.8%) reported *regularly.* A large proportion of the participants reported they did not act upon this information practice of active scanning, with eleven participants (40.7%) reporting *never* and seven participants (25.9%) reporting that they *rarely* followed friends' Fitbit data to see their daily steps and information about wearable activity trackers. Eleven participants (40.7%) *rarely* received information about exercise and wearable activity trackers by chance when reading friends' posts on social media and from other people. Regarding whether participants received information by chance through social media or from other people, seven (25.9%) reported *sometimes,* and four participants (14.8%) reported *rarely*. Through the by-proxy information practices, ten participants (37.0%) *sometimes* asked other people to find information about exercise and wearable activity trackers.

Of the total participants, eleven (40.7%) had *never* shared their tracking data with friends or posted their tracking data on social media. By contrast, ten participants (30.7%) *often* shared their data with friends or posted the data on social media.

## Table 4.6 Information Practices of Adopters(n=27)

| **Information Practices** | **Never** n (%) | **Rarely** n (%) | **Sometimes** n (%) | **Often** n (%) | **Regularly** n (%) |
|---|---|---|---|---|---|
| **Information needs** *I am interested in information concerning physical activity (PA) and wearable activity tracker (Fitbit) or feel like I should know more about it.* | 0 (0%) | 1 (3.7%) | 3 (11.1%) | 12 (44.4%) | 11 (40.7%) |
| **Active seeking** *I have been searching to find whether other people posted articles about wearable activity tracker and to find whether there was a discussion group/forum page about wearable activity tracker.* | 3 (11.1%) | 4 (14.8%) | 7 (25.9%) | 9 (33.3%) | 4 (14.8%) |
| **Active scanning** *I'm following friends' Fitbit to see his/her daily steps and I'm following information about activity tracking devices.* | 11 (40.7%) | 7 (25.9%) | 3 (11.1%) | 6 (22.2%) | 0 (0%) |
| **Nondirected monitoring** *I receive information about exercise and wearable activity tracker by chance when reading friend's post on social media and by chance from other people.* | 4 (14.8%) | 11(40.7%) | 7 (25.9%) | 4 (14.8%) | 1(3.7%) |
| **By proxy** *I have asked other people to find me information about exercise and wearable activity tracker.* | 6 (22.2%) | 6 (22.2%) | 10 (37.0%) | 5 (18.5%) | 0 (0%) |
| **Sharing information** *I have been sharing my tracking data with friends.* *I have been posting my tracking data on social media (Facebook or Twitter)* | 11 (40.7%) | 4 (14.8%) | 1 (3.7%) | 10 (37.0%) | 1 (3.7%) |
| **Participating** I'm participating in social networks or discussion groups related to Fitbit. | 7 (25.9%) | 3 (11.1%) | 5 (18.5%) | 7 (25.9%) | 5 (18.5%) |

### 4.2 Results of Ecological Momentary Assessment (EMA) Data

Participants ($N = 27$) answered 100% of EMA prompts ($n = 270$) for 5 days. 27 participants had physical activity data from wearable activity tracker (Fitbit) including steps and intensity level of physical activity (minutes of lightly/fairly/very active) were matched with data from the EMA prompts ($n = 270$).

#### 4.2.1 Descriptive Statistics Results of EMA Data

##### 4.2.1.1 Contexts and Environmental Factors from Morning EMA Questionnaire

Overall, a proportion of the morning EMA survey prompts (morning questions sent out by 8-9 am and that were completed and submitted before 11 am) included participants' reports of their main activities right before the survey (Q. "*What were you doing right before the survey prompts?"*), and the prompts were as follows: computer work (58.5%); on the way to work (24.4%); taking a rest (5.9%); and having a meal (4.4%). The top two transportation methods for arriving at work were *bus* (28.1%) and a *car* (28.1%) (Table 4.7). Regarding the survey prompts from the morning participants usually felt *good* (34.6%) and *tired* (31.9%), and their current stress level was *least stressed* (40%), *somewhat stressed* (23.7%), and *extremely stressed* (18.5%). In the morning, participants checked their data at least once (77.1%) through the Fitbit device (56.4%) and Fitbit mobile app (42.1%). Interestingly, only a very few participants checked their data via PC (1.4%). Steps data (44.3%) were most checked in the morning, followed by sleep (28.9%), heart rate (9.5%), calories (9.0%), and distance (6.5%). Participants usually performed Very Light (40.8%) (e.g., reading, standing, talking, sitting in office, studying) and Light (40.8%) (e.g., walking at a slow pace, light office work) levels of PA in the morning. In the morning, participants reported they typically performed PA such as walking to the office when commuting (40.1%) and taking a walk within the company (33.82%).

**Table 4.7 Descriptive Statistics for Morning EMA: Participants (N = 27) answered 100 % of Morning EMA prompts (n=135)**

| EMA Morning Questions | Frequency | Percentage Frequency (%) |
|---|---|---|
| *What were you doing right before the survey prompts?* | | |
| Computer work | 79 | 58.5 |
| On the way to work | 33 | 24.4 |
| Taking a rest | 8 | 5.9 |
| Having meals | 6 | 4.4 |
| Drinking water | 2 | 1.5 |
| Chatting with colleagues | 1 | 0.7 |
| Having a Meeting | 2 | 1.5 |
| Others | 4 | 3.0 |
| *Did you arrive at work?* | | |
| Yes | 102 | 75.6 |
| No | 3 | 2.2 |
| On my way to work | 30 | 22.2 |
| *Transportation regime* | | |
| Before I go to work | 3 | 2.2 |
| Bus | 38 | 28.1 |
| Subway | 13 | 9.6 |
| Bus + subway | 18 | 13.3 |
| Bicycle | 9 | 6.7 |
| On foot | 12 | 8.9 |
| Car | 38 | 28.1 |
| Electric kickboard | 4 | 3.0 |
| *How do you feel now?** | | |
| Good | 63 | 34.6 |
| Joyful | 18 | 9.9 |
| Nervous | 15 | 8.2 |
| Tired | 58 | 31.9 |
| Depressed | 5 | 2.7 |
| Annoyed | 7 | 3.8 |
| Upset | 5 | 2.7 |
| Other | 11 | 6.0 |
| *Rate your current stress level?* + | | |
| 1 (not at all) | 21 | 15.6 |
| 2 (Least stressed) | 54 | 40.0 |
| 3 (Somewhat stressed) | 32 | 23.7 |
| 4 (Extremely stressed) | 25 | 18.5 |
| 5 (Most stressed) | 3 | 2.2 |

| | | |
|---|---|---|
| *Have you checked your data from Fitbit this?* | | |
| No | 31 | 22.9 |
| Yes, once | 58 | 43.0 |
| Yes, Twice | 34 | 25.2 |
| Yes, more than 3 times | 12 | 8.9 |
| *In what way did you check your data?* | | |
| Via Fitbit Device | 79 | 56.4 |
| Via Fitbit Mobile app | 59 | 42.1 |
| Via PC | 2 | 1.4 |
| *Type of data you checked this morning** | | |
| Steps | 89 | 44.3 |
| Heart Rates | 19 | 9.5 |
| Distance | 13 | 6.5 |
| Calories | 18 | 9.0 |
| Sleep | 58 | 28.9 |
| Others | 4 | 2.0 |
| *Level of physical activities you did this morning* | | |
| Very light | 89 | 40.8 |
| Light | 89 | 40.8 |
| Light plus | 23 | 10.6 |
| Moderately Vigorous | 6 | 2.8 |
| Moderately Vigorous Plus | 8 | 3.7 |
| Vigorous | 3 | 1.4 |
| *All of the physical activities in the morning** | | |
| Walking to the office when commuting | 83 | 40.1 |
| Go to the gym to work out | 7 | 3.4 |
| Use stairs instead of elevators | 33 | 15.9 |
| Participate in exercise programs at work | 2 | 1.0 |
| Take a walk in the company | 70 | 33.82 |
| Other (e.g., riding bicycle) | 12 | 5.80 |
| *How did you feel when you checked the data provided by Fitbit?* | | |
| It motivates me a lot | 81 | 60.0 |
| It motivates me a little | 43 | 31.85 |
| It does not motivate me at all | 1 | 0.74 |
| I have no idea | 6 | 4.44 |
| Other | 4 | 2.97 |

$^{+}$ Likert Scale (1: Not at all, 5: Most stressed) * Multiple selections possible

#### 4.2.1.2 Contexts and Environmental Factors from Evening EMA Questionnaire

Compared to the morning EMA survey results, overall, the proportion of evening EMA survey prompts (evening questions sent out by 6-7pm and what were completed and submitted before 9pm) included participants' reports of their main activities right before the survey (Q. "*What were you doing right before the survey prompts?"),* and the prompts were as follows: leaving work (32.6%); computer work (25.2%); doing housework (cleaning, cooking, etc.) (18.5%); eating meals (12.6%); and working out/exercising (7.4%). Similar to the morning mood, regarding the survey prompts in the evening, participants usually felt *good* (39.1%) and *tired* (31.5%). Participants reported that they worked on that day for 8 hours (57%), 9 hours (25.9%), 10 hours (12.6%), and 11 hours (4.4%). I asked them to provide their sedentary time during their work on that day: 7 hours (37.85%) was the most common answer, which indicated that participants were sitting for most of their work time. This was followed by 5 hours (23%), 6 hours (20.7%), 8 hours (11.9%), and 9 hours (5.9%). For the evening EMA, I asked how many times participants checked their data on that day (multiple selections were possible) and with which channel (Fitbit device, mobile app, or PC). The Fitbit device was checked at least once (94.8%) and more than five times (25.2%). Only 5.2% did not check the data through the Fitbit device. The Fitbit mobile app was checked at least once with 71.1% responses and more than five times with 8.1% responses. 28.9% did not check through the mobile app. A similar result was found for the morning EMA, as 87.4% did not check their data through a PC/website during the evening EMA survey period. Only 12.6% checked at least once. The findings of the EMA results are consistent with the results of the qualitative interview data. During the interview, participants also indicated that they did not usually check and review their data through a PC.

Twenty one and a half percent of responses indicated that participants shared their data or competed with their Fitbit friends, and 78.5% did not. Similar to the morning, participants usually performed a Very Light (41.1%) (e.g., reading, standing, talking, sitting in office, studying) and Light (37.7%) (e.g., walking at a slow pace, light office work) level of PA. In the pre-questionnaire, I asked participants about their favorite type of PA level (see Table 4.3), and the proportion of responses for Moderately Vigorous, Moderately Vigorous Plus, and Vigorous was considerable (51.8%). Nevertheless, during the morning and evening EMA survey periods, the PA level was mainly focused on Very Light and Light. This result could be due to the fact that the participants were mostly sitting or performed minimal PA during work. During work time, participants reported that they typically performed PA such as taking a walk within the company (37.9%), walking to the office when commuting (33.0%), using the stairs instead of the elevator (18.6%), and going to the gym to work out.

**Table 4.8 Descriptive Statistics for Evening EMA: Participants (N = 27) answered 100 % of Evening EMA prompts (n=135)**

| EMA Evening Questions | Frequency | Percentage Frequency (%) |
|---|---|---|
| *What were you doing right before survey prompts?* | | |
| Computer work | 34 | 25.2 |
| Leaving work | 44 | 32.6 |
| Taking a rest | 3 | 2.2 |
| Having meals | 17 | 12.6 |
| Doing Housework (cleaning, cooking, etc.) | 25 | 18.5 |
| Having a meeting | 2 | 1.5 |
| Working out | 10 | 7.4 |
| *Did you leave work?* | | |
| Yes | 53 | 39.3 |
| No | 36 | 26.7 |
| I'm leaving work now | 46 | 34.1 |
| *How do you feel now? ** | | |
| Good | 72 | 39.1 |
| Joyful | 25 | 13.6 |
| Nervous | 9 | 4.9 |
| Tired | 58 | 31.5 |
| Depressed | 2 | 1.1 |
| Annoyed | 8 | 4.3 |
| Upset | 4 | 2.2 |
| Other | 6 | 3.3 |

| | | |
|---|---|---|
| *How many hours did you work today?* | | |
| 8 hours | 77 | 57.0 |
| 9 hours | 35 | 25.9 |
| 10 hours | 17 | 12.6 |
| 11 hours | 6 | 4.4 |
| *How long have you been sitting all day today?* | | |
| 5 hours | 31 | 23.0 |
| 6 hours | 28 | 20.7 |
| 7 hours | 51 | 37.8 |
| 8 hours | 16 | 11.9 |
| 9 hours | 8 | 5.9 |
| More than 10 hours | 1 | 0.7 |
| *What is your stress level today?* + | | |
| 1 (not at all) | 13 | 9.6 |
| 2 (Least stressed) | 52 | 38.5 |
| 3 (Somewhat stressed) | 41 | 30.4 |
| 4 (Extremely stressed) | 25 | 18.5 |
| 5 (Most stressed) | 4 | 3.0 |
| *Check all the data you have checked today* * | | |
| Steps | 127 | 40.6 |
| Heart Rates | 51 | 16.3 |
| Distance | 36 | 11.5 |
| Calories | 34 | 10.9 |
| Sleep | 63 | 20.1 |
| Others | 2 | 0.6 |
| *How many times have you checked your data via Fitbit device display today?* | | |
| No | 7 | 5.2 |
| Once | 26 | 19.3 |
| Twice | 36 | 26.7 |
| Three times | 20 | 14.8 |
| Four times | 12 | 8.9 |
| More than five time | 34 | 25.2 |
| *How many times have you checked your data via Fitbit Mobile App?* | | |
| No | 39 | 28.9 |
| Once | 35 | 25.9 |
| Twice | 25 | 18.5 |
| Three times | 19 | 14.1 |
| Four times | 6 | 4.4 |
| More than five times | 11 | 8.1 |

| | | |
|---|---|---|
| *How many times have you checked your data via Fitbit Website (on PC)?* | | |
| No | 118 | 87.4 |
| Once | 16 | 11.9 |
| Twice | 1 | 0.7 |
| Three times | 0 | 0 |
| Four times | 0 | 0 |
| *Did you share data or compete with your Fitbit friends?* | | |
| *Yes* | 29 | 21.5 |
| *No* | 106 | 78.5 |
| *Level of physical activities you did in the afternoon** | | |
| Very light | 109 | 41.1 |
| Light | 100 | 37.7 |
| Light plus | 37 | 14.0 |
| Moderately Vigorous | 7 | 2.6 |
| Moderately Vigorous Plus | 4 | 1.5 |
| Vigorous | 8 | 3.0 |
| *All of the physical activities for the whole day today** | | |
| Walking to the office when commuting | 87 | 33.0 |
| Go to the gym to work out | 12 | 4.5 |
| Use stairs instead of elevators | 49 | 18.6 |
| Participate in exercise programs at work | 1 | 0.4 |
| Take a walk in the company | 100 | 37.9 |
| Other (e.g., riding bicycle) | 15 | 5.7 |
| *Weather Today* | | |
| Clear | 87 | 64.4 |
| Cloudy | 25 | 18.5 |
| Raining a little and cloudy | 12 | 8.9 |
| Raining heavy | 1 | 0.7 |
| Snowy | 2 | 1.5 |
| Extremely cold | 7 | 5.2 |
| Yellow dust | 1 | 0.7 |

$^{+}$ Likert Scale (1: Not at all, 5: Most stressed), * Multiple selections possible

### 4.2.2 Inferential Statistics Results of EMA Data

#### 4.2.2.1 EMA Morning Questionnaire Data and Self-Reported Steps Counts from Fitbit

The independent variables retrieved from the EMA Morning Questionnaire are; 1) mood state in the morning; 2) the device (Fitbit device/ mobile app/ website) used to check the data; 3) physical activity level that was mainly done in the morning, 4) physical activity performed on the way to work or at the office in the morning, 5) stress level, 6) how they feel when they check their data, 7) transportation used for coming to work, and 8) weather . The Linear Mixed Model (LMM) was used to determine the interaction with the number of steps (dependent variable) that were reported by the user after checking the step data on the Fitbit device during the morning EMA survey. The table below shows the independent variables in the LMM that had a statistically significant interaction with the dependent variable (number of steps reported by user after checking the step data on the Fitbit device during the morning EMA survey). For readability, the table shows results rounded to two decimal places, except P value.

**Table 4.9 The independent variables (Morning EMA) that had an effect with 95% confidence interval: Relations between morning EMA and self-reported steps counts from Fitbit**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | 1229.71 | 1300.06 | 25.72 | .94 | .35 | -1444.04 | 3903.45 |
| [Mood state: Good] | -842.30 | 395.20 | 26.95 | -2.13 | .042* | -1653.25 | -31.35 |
| [Mood state: Joyful] | -901.18 | 509.24 | 43.07 | -1.77 | .084 | -1928.10 | 125.75 |
| [Mood state: Nervous] | 387.91 | 479.60 | 45.28 | .81 | .421 | -577.89 | 1353.72 |
| [Mood state: Tired] | -789.26 | 383.32 | 42.46 | -2.06 | .046* | -1562.58 | -15.94 |
| [Mood state: Depressed] | -3236.69 | 1690.39 | 44.66 | -1.92 | .062 | -6642.02 | 168.65 |
| [Mood state: Annoyed] | -457.10 | 978.31 | 36.17 | -.47 | .643 | -2440.88 | 1526.69 |
| [Mood state: Upset] | 1787.33 | 1471.56 | 26.86 | 1.22 | .235 | -1232.81 | 4807.47 |
| [Mood state: Other] | 359.52 | 567.05 | 25.71 | .63 | .532 | -806.71 | 1525.75 |
| [Checked data via Fitbit device] | 305.48 | 425.70 | 39.46 | .72 | .477 | -555.26 | 1166.22 |
| [Checked data via Fitbit app] | 415.70 | 404.21 | 31.85 | 1.03 | .312 | -407.80 | 1239.19 |
| [Checked data via PC] | -605.71 | 848.81 | 30.49 | -.71 | .481 | -2338.05 | 1126.64 |
| [Physical activity level: Very Light] | -1309.75 | 352.35 | 38.75 | -3.72 | .001** | -2022.58 | -596.92 |
| [Physical activity level: Light] | -338.69 | 460.28 | 55.14 | -.74 | .465 | -1261.07 | 583.69 |
| [Physical activity level: Light Plus] | -122.05 | 422.53 | 53.08 | -.29 | .774 | -969.51 | 725.41 |
| [Physical activity level: Moderately Vigorous] | 3615.13 | 2567.71 | 55.89 | 1.41 | .165 | -1528.84 | 8759.10 |
| [Physical activity level: Moderately Vigorous Plus] | 9837.67 | 2380.66 | 41.68 | 4.13 | .000** | 5032.20 | 14643.13 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Physical activity level: Vigorous] | 7328.83 | 2373.86 | 41.21 | 3.09 | .004** | 2535.49 | 12122.18 |
| [Walking to the office when commuting] | -132.85 | 571.83 | 44.90 | -.23 | .817 | -1284.65 | 1018.94 |
| [Go to the gym to work out] | -1546.58 | 2037.04 | 45.46 | -.76 | .452 | -5648.24 | 2555.08 |
| [Use stairs instead of elevators] | 315.18 | 358.35 | 28.77 | .88 | .386 | -417.98 | 1048.34 |
| [Take a walk in the company] | 535.52 | 457.79 | 53.73 | 1.17 | .247 | -382.40 | 1453.44 |
| [Other (e.g., riding bicycle)] | -4109.72 | 1216.73 | 50.02 | -3.38 | .121 | -6553.58 | -1665.86 |
| [Transportation regime: Bus] | 924.42 | 1333.94 | 43.96 | .69 | .492 | -1764.03 | 3612.88 |
| [Transportation regime: Subway] | 1721.50 | 1558.26 | 43.71 | 1.11 | .275 | -1419.57 | 4862.56 |
| [Transportation regime: Bus + subway] | 56.29 | 1359.89 | 38.05 | .041 | .967 | -2696.53 | 2809.11 |
| [Transportation regime: Bicycle] | -3143.05 | 2186.22 | 41.69 | -1.44 | .158 | -7555.99 | 1269.89 |
| [Transportation regime: On foot] | 2011.21 | 1483.66 | 43.01 | 1.36 | .182 | -980.86 | 5003.278 |
| [Transportation regime: Car] | -394.31 | 1137.37 | 38.64 | -.35 | .731 | -2695.54 | 1906.93 |
| [Transportation regime: Electric kickboard] | 43.23 | 1249.42 | 37.35 | 1.01 | .143 | -1321.43 | 3521.32 |
| Level of Stress | 17.88 | 220.54 | 37.06 | .081 | .936 | -428.95 | 464.71 |
| Number of checked Fitbit data | 202.52 | 256.94 | 36.74 | .788 | .436 | -318.21 | 723.25 |
| Weather | 32.90 | 151.81 | 38.15 | .215 | .831 | -274.70 | 339.87 |
| Feelings checked data: Motivated | 550.54 | 310.37 | 49.07 | 1.77 | .082 | -73.15 | 1174.23 |

*p<0.05, **p<0.01

Among the significant results, the *good* and *tired* mood states interact with the number of steps in the morning. The result of *good* mood was -842,30 ($p<0.05$) while it was -789.25 ($p<0.05$) for being *tired*. Other mood states showed no effect.

In terms of physical activity performed during the morning, Very Light (e.g., reading, talking, sitting in the office, studying), Moderately Vigorous Plus (e.g., swimming, tennis, dancing), and Vigorous (e.g., hiking, skiing, jogging) activities have demonstrated a statistically significant interaction with the number of steps in the morning. In other words, when participants reported to the morning survey that they mainly did the Very Light physical activity (sitting in the office) in the morning, they were found to walk less -1309.75 ($p<0.01$), while the activity of Moderately Vigorous Plus level walked more by 9837.66 ($p<0.01$). The Vigorous activities walked 7328.83 ($p<0.01$) more. The results illustrate that sitting in an office has an interaction with lower number of steps taken by research participants. On the other hand, Moderately Vigorous Plus and Vigorous levels of physical activity show around 10,000 more steps, which is a huge difference. Other physical activities were found to have no effect.

#### 4.2.2.2 EMA Evening Questionnaire Data and Self-Reported Steps Counts from Fitbit

The independent variables retrieved from the EMA Evening Questionnaire are; 1) whether the participant had left the office or not, 2) mood state, 3) data type checked, 4) whether the participant competed with a friend via Fitbit app, 5) physical activity level that was mainly done in the afternoon, 6) work hours, 7) sitting time, 8) stress level, 9) the device (Fitbit device/ mobile app/ website) used to check the data, and 9) weather. As in the morning, the linear mixed model was used to determine the interaction of above independent variables on the number of steps (dependent variable) that were reported by the user after checking the step data on the Fitbit device during the evening EMA survey.

**Table 4.10 The independent variables (Evening EMA) that had an effect with 95% confidence interval: Relations between evening EMA and self-reported steps counts from Fitbit**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | 3560.11 | 4885.56 | 24.02 | .729 | .473 | -6522.83 | 13643.05 |
| [Left the office=Yes] | 1894.61 | 600.75 | 14.41 | 3.15 | .007** | 609.57 | 3179.66 |
| [Mood state: Good] | -1041.44 | 786.51 | 9.66 | -1.32 | .216 | -2802.40 | 719.522 |
| [Mood state: Joyful] | -2249.18 | 862.63 | 19.81 | -2.61 | .017** | -4049.69 | -448.66 |
| [Mood state: Nervous] | -1948.60 | 2270.87 | 21.51 | -.86 | .400 | -6664.30 | 2767.09 |
| [Mood state: Tired] | -15.76 | 705.98 | 8.19 | -.02 | .983 | -1637.17 | 1605.65 |
| [Mood state: Depressed] | -6611.10 | 3400.08 | 17.32 | -1.94 | .068 | -13774.58 | 552.38 |
| [Mood state: Annoyed] | 279.37 | 1696.26 | 37.44 | .16 | .870 | -3156.21 | 3714.95 |
| [Mood state: Upset] | -540.19 | 4235.69 | 14.85 | -.13 | .900 | -9576.34 | 8495.96 |
| [Mood state: Other] | 907.19 | 4604.82 | 16.92 | .20 | .846 | -8811.81 | 10626.19 |
| [Competed using Fitbit=Yes] | 2292.83 | 778.46 | 15.78 | 2.95 | .010** | 640.66 | 3945.00 |
| [Physical activity level: Very Light] | 1290.27 | 1142.88 | 18.11 | 1.13 | .274 | -1109.82 | 3690.37 |
| [Physical activity level: Light] | 489.87 | 966.91 | 28.97 | .51 | .616 | -1487.76 | 2467.50 |
| [Physical activity level: Light Plus] | -1334.40 | 734.94 | 11.96 | -1.82 | .095 | -2936.32 | 267.52 |
| [Physical activity level: Moderately Vigorous] | 1804.14 | 1457.24 | 31.83 | 1.24 | .225 | -1164.80 | 4773.08 |
| [Physical activity level: Moderately Vigorous Plus] | 5861.87 | 2183.93 | 33.62 | 2.68 | .011** | 1421.73 | 10302.01 |
| [Physical activity level: Vigorous] | 311.94 | 1762.35 | 31.56 | .18 | .861 | -3279.82 | 3903.70 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Physical Activity: Walking to the office when commuting] | 1125.65 | 843.70 | 17.53 | 1.33 | .199 | -650.271 | 2901.58 |
| [Physical Activity: Go to the gym to work out] | 461.50 | 1780.71 | 34.45 | .26 | .797 | -3155.59 | 4078.59 |
| [Physical Activity: Use stairs instead of elevators] | 1877.83 | 830.91 | 20.19 | 2.26 | .035* | 145.62 | 3610.041 |
| [Physical Activity: Take a walk in the company] | 169.81 | 811.456 | 26.84 | .21 | .836 | -1495.63 | 1835.25 |
| [Physical Activity: Other (e.g., riding bicycle)] | 3555.60 | 1132.67 | 16.21 | 3.14 | .006** | 1156.96 | 5954.24 |
| Total Working Hours of the day | 497.63 | 403.02 | 18.00 | 1.24 | .233 | -349.08 | 1344.34 |
| Total Sedentary Time | -140.62 | 377.91 | 23.49 | -.37 | .713 | -921.49 | 640.25 |
| Level of Stress | -678.37 | 426.93 | 34.67 | -1.59 | .121 | -1545.38 | 188.64 |
| Number of checked Fitbit data via Device | 218.71 | 202.49 | 5.37 | 1.08 | .326 | -291.20 | 728.62 |
| Number of checked Fitbit data via App | -227.10 | 463.53 | 41.22 | -.49 | .627 | -1163.06 | 708.86 |
| Number of checked Fitbit data via PC/Web | -238.98 | 1519.32 | 20.46 | -.16 | .877 | -3403.66 | 2925.70 |
| Weather | -30.35 | 229.87 | 25.63 | -.13 | .896 | -503.12 | 442.50 |

*p<0.05, **p<0.01

First, in terms of leaving work, it has an interaction with the number of steps in the evening. In other words, one would walk more by 1894.61 ($p<0.01$) when leaving work early.

When considering the level of physical activity in the evening, similar to the morning survey results, it is found that the Moderately Vigorous Plus activity level (e.g., swimming, tennis, dancing) has a statistically significant interaction with the number of steps in the evening ( more walking by 5861.87 ($p<0.01$)).

Among different mood states, *joyful* has a statistically significant interaction with the number of steps in the afternoon. It means that in an enjoyable mood, one would walk less by -2249.17 ($p<0.01$).

Further, regarding the question that asks whether the participant had competed using the Fitbit app during the day, the competing experience has an interaction with the number of steps. Statistically, when the participant competed, he or she would walk more by 2292.82 ($p<0.01$).

In terms of the physical activity that participants did during that day, using stairs instead of the elevators has a statistically significant interaction with the number of steps during that day (walked more by 1877.83 ($p<0.05$)).

**Table 4.11 Summary of relation between EMA Morning and Evening Independent Variables and Morning and Evening Self-report Steps Counts**

| Dependent Variables | Independent Variables |
|---|---|
| ***1. Morning Steps Data*** *:Reported by the user after checking the step data on the Fitbit device during the morning EMA survey* | **From Morning EMA**<br>[**Morning** Mood state: Good] **Negative**<br>[**Morning** Mood state: Tired] **Negative**<br>[**Morning** Physical activity level: Very Light] **Negative**<br>[**Morning** Physical activity level: Moderately Vigorous Plus] **Positive**<br>[**Morning** Physical activity level: Vigorous] **Positive** |
| ***2. Evening Steps Data*** ***:*** *Reported by the user after checking the step data on the Fitbit device during the evening EMA survey* | **From Evening EMA**<br>[**Evening** Left the office = Yes] **Positive**<br>[**Evening** Mood state: Joyful] **Negative**<br>[**Evening** Physical activity level: Moderately Vigorous Plus] **Positive**<br>[**Today** Competed using Fitbit app] **Positive**<br>[**Today** Physical Activity: Use stairs instead of elevators] **Positive**<br>[**Today** Physical Activity: Other (e.g., riding bicycle)] **Positive** |

**Discussion: Underestimated the number of steps**

The EMA morning and evening survey asked to guess how many steps the participant had taken and report actual number of steps from Fitbit. The t-test was used here to compare their predictions with the actual number of steps to see whether they are overestimated or underestimated.

**Table 4.12 Relationship between Prediction and Actual Step Counts**

| Variable | Prediction | | Actual number | | t | p |
|---|---|---|---|---|---|---|
| | Average | SD | Average | SD | | |
| Morning | 2223.11 | 2436.093 | 2721.42 | 2792,055 | -7.286 | .000** |
| Evening | 7363.70 | 7488,543 | 8143.68 | 4491.98 | -1.393 | .166 |

*p<0.05, **p<0.01

The above table compares the difference between the prediction and the actual number of steps. In the morning, the prediction average was 2223.11 and the actual average was 2721.42. In the test statistic, the t-value is -7.286 and the significance probability is 0.000, which is a statistically significant difference. There is a real difference between predictions and reality.

In the evening, the predictions averaged 7363.70 and the actual average was 8143.68. The test statistic shows no statistically significant difference as t-value is -1.393 while significance probability is 0.166.

Both in morning and evening results, most research participants were underestimating the number of steps they took. For the mornings, the predicted average was 18.31% less than the actual average. Otherwise, in the evening the predicted average was 9.58% less than the actual average number of steps. It's more likely that underestimating is a common error in general.

My results are in line with the previous study that also discovered that the majority of young and middle-aged to old adults underestimated their physical activity (Canning et al., 2014). An accurate assessment is critical for increasing physical activity (Prince et al., 2008); a wearable activity tracker could be used to complete objective measurement.

#### 4.2.2.3 Analysis of Fitbit Data for the Day and EMA Data

During EMA survey period, the participants have submitted their Fitbit data (steps, activities-minutes of lightly active, fairly active, and very active) for the whole period of using the device, including the data for 5 days of EMA survey period. The Fitbit data for the 5 days of EMA study were used to determine how independent variable of both morning and evening interacted with the total number of steps taken on that day. Linear Mixed Model analysis was used as above.

1) The effect of morning EMA independent variables on total *steps* of the day

According to the data provided by Fitbit, the answer to the question of *"How did you feel when you checked the data provided by Fitbit? (answer choices: 1) Motivates me a lot, 2) motivates me a little, 3) does not motivate me at all, and 4) I have no idea) "* had an interaction with the number of *steps* of the day. When participants reported that they were motivated when they checked their data in the morning, the participant walked more by 2771.41($p<0.01$) of the day.

**Table 4.13 Relationship between Morning EMA Independent Variables and Steps of the Day**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | -4369.30 | 8595.72 | 42.140 | -.508 | .614 | -21714.46 | 12975.87 |
| [Transportation regime: Bus] | 6357.88 | 7028.61 | 23.49 | .91 | .375 | -8165.02 | 20880.79 |
| [Transportation regime: Subway] | 7377.126 | 7009.27 | 24.30 | 1.05 | .303 | -7079.87 | 21834.10 |
| [Transportation regime: Bus + subway] | 5856.27 | 7033.26 | 24.39 | .83 | .413 | -8647.31 | 20359.84 |
| [Transportation regime: Bicycle] | -8396.74 | 6990.35 | 22.71 | -1.20 | .242 | -22867.53 | 6074.06 |
| [Transportation regime: On foot] | 5330.01 | 7288.69 | 26.33 | .73 | .471 | -9642.87 | 20302.89 |
| [Transportation regime: Car] | 5357.85 | 6897.66 | 23.15 | .78 | .445 | -8906.07 | 19621.78 |
| [Transportation regime: Electric kickboard] | 1995.40 | 7807.66 | 33.69 | .26 | .800 | -13876.99 | 17867.79 |
| [Mood state: Good] | 103.25 | 1698.63 | 58.88 | .06 | .952 | -3295.86 | 3502.35 |
| [Mood state: Joyful] | -2415.50 | 2140.52 | 58.06 | -1.13 | .264 | -6700.12 | 1869.13 |
| [Mood state: Nervous] | -321.18 | 1835.83 | 47.36 | -.18 | .862 | -4013.66 | 3371.30 |
| [Mood state: Tired] | -286.49 | 1490.39 | 60.29 | -.19 | .848 | -3267.423 | 2694.44 |
| [Mood state: Depressed] | -8646.761 | 5974.84 | 17.58 | -1.45 | .165 | -21220.80 | 3927.28 |
| [Mood state: Annoyed] | 6603.93 | 3815.29 | 29.24 | 1.73 | .094 | -1196.45 | 14404.31 |
| [Mood state: Upset] | 3698.95 | 7086.65 | 30.42 | .52 | .605 | -10765.46 | 18163.37 |
| [Mood state: Other] | 732.51 | 2398.52 | 59.02 | .31 | .761 | -4066.87 | 5531.89 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Checked data via Fitbit device] | 1853.32 | 1738.42 | 49.72 | 1.07 | .292 | -1638.88 | 5345.51 |
| [Checked data via Fitbit app] | 992.54 | 1557.76 | 61.32 | .64 | .526 | -2122.06 | 4107.14 |
| [Checked data via PC] | 746.97 | 3889.23 | 27.54 | .19 | .849 | -7225.73 | 8719.66 |
| [Physical activity level: Very Light] | -2160.93 | 1490.28 | 51.08 | -1.40 | .153 | -5152.67 | 830.81 |
| [Physical activity level: Light] | 1143.08 | 1687.02 | 63.86 | .68 | .500 | -2227.27 | 4513.42 |
| [Physical activity level: Light Plus] | -1306.87 | 1658.31 | 44.21 | -.79 | .435 | -4648.53 | 2034.80 |
| [Physical activity level: Moderately Vigorous] | 11520.17 | 6435.80 | 27.47 | 1.70 | .084 | -1674.55 | 24714.88 |
| [Physical activity level: Moderately Vigorous Plus] | 4548.04 | 3185.12 | 48.65 | 1.43 | .160 | -1853.87 | 10949.95 |
| [Physical activity level: Vigorous] | 721.159 | 5063.125 | 35.24 | .14 | .888 | -9554.97 | 10997.29 |
| [Physical Activity: Walking to the office when commuting] | -1963.64 | 2201.68 | 56.31 | -.89 | .376 | -6373.61 | 2446.33 |
| [Physical Activity: Go to the gym to work out] | -1242.56 | 1407.98 | 49.54 | -.88 | .382 | -4071.22 | 1586.09 |
| [Physical Activity: Use stairs instead of elevators] | -572.59 | 4631.54 | 26.55 | -.12 | .903 | -10083.21 | 8938.03 |
| [Physical Activity: Take a walk in the company] | 162.35 | 1448.57 | 62.30 | .11 | .911 | -2733.01 | 3057.71 |
| [Physical Activity: Other (e.g., riding bicycle)] | 2641.28 | 4381.68 | 40.66 | .60 | .550 | -6209.94 | 11492.50 |
| Level of Stress | -930.64 | 845.97 | 62.77 | -1.10 | .276 | -2621.30 | 760.03 |
| Number of checked Fitbit data | 1883.01 | 993.89 | 45.56 | 1.90 | .065 | -118.10 | 3884.13 |
| Feelings checked data: Motivated | 2771.42 | 1109.05 | 56.20 | 2.50 | .015* | 549.90 | 4992.94 |

*p<0.05, **p<0.01

2) The effect of **morning** EMA independent variable on total activity minutes of ***all of the activity level* (lightly/fairly/very) as a single group** of the day

Fitbit provided total activity minutes that combined with lightly, fairly, and very active minutes. This section describes the interaction with *total active minutes* as dependent variables and morning EMA as independent variables. Similar to interaction with *total steps of the day* and morning EMA data, the answers to the question of *"How do you feel when you checked the data provided by Fitbit"* had an interaction with total activite minutes in the morning. When participants reported that they were motivated when they checked their data in the morning, the positive interaction of 60.58 ($p < .01$) on total active minutes was observed.

**Table 4.14 Relationship between Morning EMA Independent Variables and All of the Activity Levels**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | -51.28 | 155.48 | 38.23 | -0.33 | .743 | -365.97 | 263.41 |
| [Transportation regime: Bus] | 118.67 | 129.83 | 25.82 | 0.91 | .369 | -148.30 | 385.64 |
| [Transportation regime: Subway] | 64.61 | 130.69 | 27.34 | 0.49 | .625 | -203.39 | 332.61 |
| [Transportation regime: Bus + subway] | 99.33 | 130.40 | 27.61 | 0.76 | .453 | -167.95 | 366.60 |
| [Transportation regime: Bicycle] | -170.02 | 227.27 | 22.30 | -0.75 | .462 | -640.99 | 300.95 |
| [Transportation regime: On foot] | 94.15 | 140.05 | 31.75 | 0.67 | .506 | -191.21 | 379.50 |
| [Transportation regime: Car] | 182.69 | 129.04 | 27.76 | 1.42 | .168 | -81.74 | 447.11 |
| [Transportation regime: Electric kickboard] | 82.30 | 148.83 | 36.85 | 0.55 | .584 | -219.30 | 383.91 |
| [Mood state: Good] | -16.44 | 34.87 | 52.94 | -0.47 | .639 | -86.39 | 53.50 |
| [Mood state: Joyful] | -21.04 | 39.94 | 43.58 | -0.53 | .601 | -101.57 | 59.48 |
| [Mood state: Nervous] | -0.82 | 34.53 | 50.15 | -0.02 | .981 | -70.17 | 68.53 |
| [Mood state: Tired] | 41.37 | 30.03 | 54.52 | 1.38 | .174 | -18.81 | 101.56 |
| [Mood state: Depressed] | -127.71 | 123.38 | 25.55 | -1.04 | .310 | -381.54 | 126.13 |
| [Mood state: Annoyed] | 146.78 | 68.86 | 23.87 | 2.13 | .054 | 4.62 | 288.95 |
| [Mood state: Upset] | 67.01 | 132.22 | 31.69 | 0.51 | .616 | -202.42 | 336.44 |
| [Mood state: Other] | 72.93 | 43.32 | 36.54 | 1.68 | .101 | -14.87 | 160.73 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Checked data via Fitbit device] | 14.61 | 29.99 | 53.05 | 0.49 | .628 | -45.55 | 74.78 |
| [Checked data via Fitbit app] | 26.92 | 26.98 | 59.42 | 1.00 | .323 | -27.07 | 80.90 |
| [Checked data via PC] | -32.41 | 66.70 | 25.46 | -0.49 | .631 | -169.65 | 104.84 |
| [Physical activity level: Very Light] | -42.61 | 29.62 | 51.88 | -1.44 | .156 | -102.05 | 16.83 |
| [Physical activity level: Light] | 27.71 | 30.44 | 51.64 | 0.91 | .367 | -33.38 | 88.79 |
| [Physical activity level: Light Plus] | 16.26 | 32.26 | 51.62 | 0.50 | .616 | -48.48 | 81.00 |
| [Physical activity level: Moderately Vigorous] | 181.47 | 251.34 | 30.08 | 0.72 | .476 | -331.77 | 694.72 |
| [Physical activity level: Moderately Vigorous Plus] | -43.28 | 154.61 | 21.27 | -0.28 | .782 | -364.56 | 278.00 |
| [Physical activity level: Vigorous] | 10.84 | 172.83 | 19.35 | 0.06 | .951 | -350.45 | 372.12 |
| [Physical Activity: Walking to the office when commuting] | -36.82 | 40.13 | 37.66 | -0.92 | .365 | -118.08 | 44.44 |
| [Physical Activity: Go to the gym to work out] | 35.58 | 144.70 | 18.21 | 0.25 | .809 | -268.18 | 339.33 |
| [Physical Activity: Use stairs instead of elevators] | -33.49 | 29.68 | 48.57 | -1.13 | .265 | -93.16 | 26.17 |
| [Physical Activity: Take a walk in the company] | 19.94 | 28.88 | 56.86 | 0.69 | .493 | -37.91 | 77.78 |
| [Physical Activity: Other (e.g., riding bicycle)] | 80.77 | 84.96 | 49.83 | 0.95 | .346 | -89.90 | 251.43 |
| Level of Stress | -18.79 | 16.59 | 51.10 | -1.13 | .263 | -52.09 | 14.52 |
| Number of checked Fitbit data | 0.01 | 0.01 | 29.48 | 1.12 | .271 | -0.01 | 23444.00 |
| Feelings checked data: Motivated | 60.58 | 21.27 | 43.80 | 2.85 | .007** | 549.90 | 4992.94 |

*p<0.05, **p<0.01

2.1) The effect of morning EMA independent variables on *activities-minutes Lightly Active* of the day

The answers to the question of "*How did you feel when you checked the data provided by Fitbit*?" had an interaction with activities-minutes Lightly Active in the morning. When participants reported that checking data was motivating them in the morning, the positive interaction of 39.622 on activities-minutes Lightly Active was observed.

**Table 4.15 Relationship between Morning EMA Independent Variables and Activities-Minutes Lightly Active**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | -100.04 | 119.90 | 42.32 | -0.83 | .409 | -341.96 | 141.88 |
| [Transportation regime: Bus] | 107.66 | 93.75 | 33.10 | 1.15 | .259 | -83.05 | 298.38 |
| [Transportation regime: Subway] | 50.58 | 93.64 | 34.86 | 0.54 | .593 | -139.55 | 240.72 |
| [Transportation regime: Bus + subway] | 103.73 | 94.17 | 33.71 | 1.10 | .278 | -87.70 | 295.16 |
| [Transportation regime: Bicycle] | -167.53 | 197.39 | 18.04 | -0.85 | .407 | -582.15 | 247.10 |
| [Transportation regime: On foot] | 102.97 | 107.43 | 37.79 | 0.96 | .344 | -114.55 | 320.49 |
| [Transportation regime: Car] | 164.80 | 95.28 | 36.89 | 1.73 | .092 | -28.28 | 357.88 |
| [Transportation regime: Electric kickboard] | 104.70 | 108.72 | 41.73 | 0.96 | .341 | -114.73 | 324.14 |
| [Mood state: Good] | -4.80 | 26.05 | 45.05 | -0.18 | .855 | -57.28 | 47.67 |
| [Mood state: Joyful] | -13.41 | 30.65 | 43.16 | -0.44 | .664 | -75.22 | 48.40 |
| [Mood state: Nervous] | 6.36 | 26.14 | 45.86 | 0.24 | .809 | -46.26 | 58.98 |
| [Mood state: Tired] | 32.53 | 21.63 | 43.60 | 1.50 | .140 | -11.07 | 76.12 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Mood state: Depressed] | -179.82 | 100.01 | 26.03 | -1.80 | .084 | -385.37 | 25.73 |
| [Mood state: Annoyed] | 115.90 | 45.10 | 20.61 | 2.57 | .118 | 22.00 | 209.79 |
| [Mood state: Upset] | 79.65 | 98.96 | 26.68 | 0.81 | .428 | -123.50 | 282.81 |
| [Mood state: Other] | 33.06 | 32.91 | 42.99 | 1.00 | .321 | -33.32 | 99.43 |
| [Checked data via Fitbit device] | 9.18 | 25.03 | 47.88 | 0.37 | .716 | -41.15 | 59.51 |
| [Checked data via Fitbit app] | 25.55 | 23.50 | 50.65 | 1.09 | .282 | -21.63 | 72.73 |
| [Checked data via PC] | -48.98 | 56.02 | 27.30 | -0.87 | .390 | -163.87 | 65.91 |
| [Physical activity level: Very Light] | -3.73 | 22.05 | 47.33 | -0.17 | .866 | -48.08 | 40.61 |
| [Physical activity level: Light] | 17.98 | 22.96 | 42.36 | 0.78 | .438 | -28.35 | 64.30 |
| [Physical activity level: Light Plus] | -2.23 | 24.77 | 49.10 | -0.09 | .929 | -52.01 | 47.55 |
| [Physical activity level: Moderately Vigorous] | 172.34 | 198.88 | 18.33 | 0.87 | .397 | -244.96 | 589.63 |
| [Physical activity level: Moderately Vigorous Plus] | 12.86 | 46.85 | 29.76 | 0.28 | .786 | -82.85 | 108.57 |
| [Physical activity level: Vigorous] | 82.11 | 68.40 | 17.39 | 1.20 | .246 | -61.95 | 226.17 |
| [Physical Activity: Walking to the office when commuting] | 5.44 | 32.32 | 44.61 | 0.17 | .867 | -59.67 | 70.56 |
| [Physical Activity: Use stairs instead of elevators] | -36.36 | 21.62 | 43.34 | -1.68 | .100 | -79.95 | 7.24 |
| [Physical Activity: Participate in exercise programs at work] | 13.66 | 60.12 | 23.70 | 0.23 | .822 | -110.50 | 137.81 |
| [Physical Activity: Take a walk in the company] | 17.96 | 21.23 | 43.73 | 0.85 | .402 | -24.83 | 60.76 |
| [Physical Activity: Other (e.g., riding bicycle)] | 97.30 | 72.43 | 58.46 | 1.34 | .184 | -47.66 | 242.26 |
| Level of Stress | -3.77 | 12.34 | 45.95 | -0.31 | .761 | -28.61 | 21.07 |
| Number of checked Fitbit data | 14.18 | 13.49 | 46.59 | 1.05 | .299 | -12.97 | 41.33 |
| Feelings checked data: Motivated | 39.62 | 16.08 | 37.44 | 2.46 | .018* | 7.05 | 72.19 |

*p<0.05, **p<0.01

2.2) The effect of morning EMA independent variables on *activities-minutes Fairly Active* of the day

The *stress* level has a statistically significant interaction with the *activities-minutes Fairly Active* in the morning. As the *stress* increased, the negative interaction of -11.286 on activities-minutes Fairly Active was observed. Conversely, when participants reported that *checking data motivated [Feelings checked data: Motivated]* a lot in the morning, activities-minutes Fairly Active had an interaction of 17.782 minutes of the day.

**Table 4.16 Relationship between Morning EMA Independent Variables and Active-Minutes Fairly Active provided by Fitbit**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | -52.70 | 48.95 | 35.52 | -1.08 | .289 | -152.02 | 46.61 |
| [Transportation regime: Bus] | 16.02 | 40.66 | 27.45 | 0.39 | .697 | -67.36 | 99.39 |
| [Transportation regime: Subway] | 10.10 | 40.88 | 28.60 | 0.25 | .807 | -73.56 | 93.76 |
| [Transportation regime: Bus + subway] | 11.45 | 40.80 | 28.85 | 0.28 | .781 | -72.02 | 94.91 |
| [Transportation regime: Bicycle] | 2.84 | 61.16 | 22.05 | 0.05 | .963 | -123.98 | 129.66 |
| [Transportation regime: On foot] | 9.34 | 44.09 | 31.49 | 0.21 | .834 | -80.53 | 99.21 |
| [Transportation regime: Car] | 21.31 | 40.61 | 29.37 | 0.53 | .604 | -61.70 | 104.32 |
| [Transportation regime: Electric kickboard] | 11.59 | 45.10 | 34.07 | 0.26 | .799 | -80.06 | 103.24 |
| [Mood state: Good] | -5.75 | 10.59 | 45.16 | -0.54 | .589 | -27.08 | 15.57 |
| [Mood state: Joyful] | -18.97 | 13.39 | 53.56 | -1.42 | .162 | -45.82 | 7.88 |
| [Mood state: Nervous] | 10.67 | 10.02 | 35.11 | 1.07 | .294 | -9.67 | 31.01 |
| [Mood state: Tired] | 9.07 | 8.59 | 34.73 | 1.06 | .298 | -8.36 | 26.50 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Mood state: Depressed] | -9.82 | 36.21 | 21.73 | -0.27 | .789 | -84.96 | 65.32 |
| [Mood state: Annoyed] | 13.94 | 17.55 | 17.75 | 0.80 | .437 | -22.96 | 50.85 |
| [Mood state: Upset] | 24.35 | 36.89 | 24.71 | 0.66 | .515 | -51.67 | 100.37 |
| [Mood state: Other] | 7.76 | 13.00 | 26.55 | 0.60 | .555 | -18.92 | 34.45 |
| [Checked data via Fitbit device] | 7.92 | 9.70 | 38.05 | 0.82 | .419 | -11.70 | 27.55 |
| [Checked data via Fitbit app] | 0.52 | 9.02 | 41.45 | 0.06 | .955 | -17.69 | 18.73 |
| [Checked data via PC] | 14.01 | 25.16 | 26.42 | 0.56 | .582 | -37.66 | 65.68 |
| [Physical activity level: Very Light] | -4.27 | 8.76 | 49.50 | -0.49 | .628 | -21.87 | 13.33 |
| [Physical activity level: Light] | 13.87 | 9.13 | 31.86 | 1.52 | .139 | -4.73 | 32.47 |
| [Physical activity level: Light Plus] | 18.13 | 9.44 | 46.42 | 1.92 | .061 | -0.87 | 37.13 |
| [Physical activity level: Moderately Vigorous] | 40.83 | 61.80 | 21.73 | 0.66 | .516 | -87.44 | 169.09 |
| [Physical activity level: Moderately Vigorous Plus] | -23.14 | 16.28 | 14.90 | -1.42 | .176 | -57.86 | 11.59 |
| [Physical activity level: Vigorous] | -6.34 | 29.69 | 21.04 | -0.21 | .833 | -68.07 | 55.39 |
| [Physical Activity: Walking to the office when commuting] | -17.60 | 13.84 | 53.59 | -1.27 | .209 | -45.35 | 10.15 |
| [Physical Activity: Use stairs instead of elevators] | -2.91 | 7.73 | 32.69 | -0.38 | .709 | -18.64 | 12.83 |
| [Physical Activity: Take a walk in the company] | 7.63 | 8.29 | 38.60 | 0.92 | .364 | -9.16 | 24.41 |
| [Physical Activity: Other (e.g., riding bicycle)] | 11.72 | 29.16 | 63.01 | 0.40 | .689 | -46.56 | 70.00 |
| Level of Stress | -11.29 | 4.76 | 36.66 | -2.37 | .023* | -20.93 | -1.64 |
| Number of checked Fitbit data | 8.90 | 5.36 | 39.58 | 1.66 | .105 | -1.94 | 19.73 |
| Feelings checked data: Motivated | 17.78 | 6.00 | 29.58 | 2.96 | .006** | 5.52 | 30.04 |

*p<0.05, **p<0.01

2.3) The effect of morning EMA independent variables on *activities-minutes Very Active*

The result in regards to whether the participant had checked Fitbit data in the morning showed that it had a statistically significant interaction on *activities-minutes Very Active* of the day. As the number of times that he or she had checked the data increased, there was a positive interaction with 12.407 minutes on *activities-minutes Very Active*.

**Table 4.17 Relationship between Morning EMA Independent Variables and Activities-Minutes Very Active**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | 49.53 | 43.46 | 33.17 | 1.14 | .263 | -38.88 | 137.94 |
| [Transportation regime: Bus] | -41.88 | 29.81 | 17.13 | -1.41 | .178 | -104.73 | 20.97 |
| [Transportation regime: Subway] | -19.62 | 31.02 | 26.38 | -0.63 | .533 | -83.35 | 44.11 |
| [Transportation regime: Bus + subway] | -49.47 | 30.21 | 16.02 | -1.64 | .121 | -113.50 | 14.55 |
| [Transportation regime: Bicycle] | -34.19 | 29.04 | 13.21 | -1.18 | .260 | -96.82 | 28.44 |
| [Transportation regime: On foot] | -21.75 | 31.55 | 21.45 | -0.69 | .498 | -87.28 | 43.78 |
| [Transportation regime: Car] | -57.62 | 28.98 | 18.99 | -1.99 | .061 | -118.27 | 3.04 |
| [Transportation regime: Electric kickboard] | -55.76 | 36.87 | 26.42 | -1.51 | .142 | -131.48 | 19.97 |
| [Mood state: Good] | 0.72 | 9.52 | 42.85 | 0.08 | .940 | -18.48 | 19.93 |
| [Mood state: Joyful] | 2.31 | 11.23 | 35.37 | 0.21 | .838 | -20.49 | 25.11 |
| [Mood state: Nervous] | -16.45 | 10.32 | 30.12 | -1.59 | .122 | -37.53 | 4.63 |
| [Mood state: Tired] | 0.01 | 8.04 | 33.04 | 0.00 | .999 | -16.35 | 16.38 |
| [Mood state: Depressed] | -54.28 | 38.96 | 23.94 | -1.39 | .176 | -134.69 | 26.14 |
| [Mood state: Annoyed] | 1.65 | 18.93 | 12.94 | 0.09 | .932 | -39.28 | 42.57 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Mood state: Upset] | 23.20 | 47.44 | 39.33 | 0.49 | .628 | -72.74 | 119.14 |
| [Mood state: Other] | -5.15 | 14.18 | 46.74 | -0.36 | .718 | -33.67 | 23.38 |
| [Checked data via Fitbit device] | 3.89 | 10.02 | 27.69 | 0.39 | .701 | -16.66 | 24.43 |
| [Checked data via Fitbit app] | 2.52 | 9.58 | 60.23 | 0.26 | .793 | -16.63 | 21.68 |
| [Checked data via PC] | 17.85 | 25.90 | 25.21 | 0.69 | .497 | -35.47 | 71.17 |
| [Physical activity level: Very Light] | -8.89 | 8.59 | 35.11 | -1.04 | .308 | -26.31 | 8.54 |
| [Physical activity level: Light] | 12.34 | 9.38 | 27.94 | 1.32 | .199 | -6.87 | 31.55 |
| [Physical activity level: Light Plus] | 8.81 | 10.76 | 51.79 | 0.82 | .417 | -12.79 | 30.40 |
| [Physical activity level: Moderately Vigorous] | 0.08 | 33.86 | 22.12 | 0.00 | .998 | -70.12 | 70.28 |
| [Physical activity level: Moderately Vigorous Plus] | 14.21 | 19.05 | 41.34 | 0.75 | .460 | -24.26 | 52.68 |
| [Physical activity level: Vigorous] | -17.73 | 20.26 | 4.41 | -0.88 | .427 | -71.98 | 36.51 |
| [Physical Activity: Walking to the office when commuting] | -27.01 | 12.32 | 42.39 | -2.19 | .346 | -51.87 | -2.16 |
| [Physical Activity: Use stairs instead of elevators] | -21.48 | 8.15 | 21.48 | -2.64 | .115 | -38.39 | -4.56 |
| [Physical Activity: Participate in exercise programs at work] | -3.42 | 18.76 | 7.98 | -0.18 | .860 | -46.69 | 39.85 |
| [Physical Activity: Take a walk in the company] | -11.97 | 7.39 | 19.08 | -1.62 | .122 | -27.43 | 3.49 |
| [Physical Activity: Other (e.g., riding bicycle)] | -22.43 | 20.13 | 21.57 | -1.11 | .278 | -64.23 | 19.38 |
| Level of Stress | -4.90 | 4.81 | 35.78 | -1.02 | .316 | -14.66 | 4.87 |
| Number of checked Fitbit data | 12.41 | 5.71 | 16.02 | 2.17 | .045* | 0.30 | 24.52 |
| Feelings checked data: Motivated | 11.75 | 6.75 | 42.84 | 1.74 | .089 | -1.87 | 25.37 |

*p<0.05, **p<0.01

3) The effect of evening EMA independent variables on the total *steps* of the day

When the participants had competed using the Fitbit app had a statistically significant interaction with the number of *steps* of the day. It appeared to positively interaction by 6407.43 steps. When participants competed using Fitbit app, the participant walked more by 6407.43 ($p<0.01$) of the day.

**Table 4.18 Relationship between Evening EMA Independent Variables and Steps of the Day**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | 7950.86 | 7093.62 | 40.04 | 1.12 | .269 | -6385.44 | 22287.17 |
| [Left the office=Yes] | 956.35 | 1264.87 | 35.13 | 0.76 | .455 | -1611.15 | 3523.85 |
| [Mood state: Good] | -4.31 | 1603.14 | 38.79 | 0.00 | .998 | -3247.52 | 3238.91 |
| [Mood state: Joyful] | 451.49 | 1669.01 | 38.15 | 0.27 | .788 | -2926.80 | 3829.78 |
| [Mood state: Nervous] | -917.50 | 2882.01 | 22.55 | -0.32 | .753 | -6885.99 | 5050.98 |
| [Mood state: Tired] | -1111.39 | 1541.20 | 25.61 | -0.72 | .477 | -4281.70 | 2058.93 |
| [Mood state: Depressed] | -8724.40 | 5586.11 | 24.66 | -1.56 | .131 | -20237.31 | 2788.52 |
| [Mood state: Annoyed] | -2351.87 | 2817.88 | 35.85 | -0.84 | .409 | -8067.66 | 3363.92 |
| [Mood state: Upset] | 1099.49 | 5634.06 | 10.04 | 0.20 | .849 | -11446.62 | 13645.59 |
| [Mood state: Other] | 343.01 | 5851.16 | 18.87 | 0.06 | .954 | -11909.48 | 12595.51 |
| [Competed using Fitbit app =Yes] | 6407.44 | 1592.13 | 30.90 | 4.02 | .000** | 3159.84 | 9655.04 |
| [Physical activity level: Very Light] | -1605.51 | 2316.02 | 30.80 | -0.69 | .493 | -6330.34 | 3119.31 |
| [Physical activity level: Light] | 2996.34 | 1715.89 | 39.66 | 1.75 | .089 | -472.55 | 6465.22 |
| [Physical activity level: Light Plus] | -1814.66 | 1478.82 | 40.37 | -1.23 | .227 | -4802.61 | 1173.29 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Physical activity level: Moderately Vigorous] | 6552.29 | 2821.35 | 29.59 | 2.32 | .027* | 787.01 | 12317.56 |
| [Physical activity level: Moderately Vigorous Plus] | -3852.16 | 4152.90 | 30.76 | -0.93 | .361 | -12324.70 | 4620.39 |
| [Physical activity level: Vigorous] | -3406.89 | 3324.93 | 46.77 | -1.03 | .311 | -10096.66 | 3282.88 |
| [Physical Activity: Walking to the office when commuting] | -1175.15 | 1704.32 | 37.69 | -0.69 | .495 | -4626.30 | 2276.00 |
| [Physical Activity: Go to the gym to work out] | -926.25 | 3294.84 | 44.00 | -0.28 | .780 | -7566.59 | 5714.09 |
| [Physical Activity: Use stairs instead of elevators] | -573.27 | 1620.00 | 43.19 | -0.35 | .725 | -3839.90 | 2693.36 |
| [Physical Activity: Take a walk in the company] | -1393.78 | 1492.20 | 37.28 | -0.93 | .356 | -4416.49 | 1628.93 |
| [Physical Activity: Other (e.g., riding bicycle)] | 4865.17 | 2459.23 | 24.88 | 1.98 | .059 | -200.91 | 9931.25 |
| Total working hours | -457.94 | 780.36 | 33.84 | -0.59 | .561 | -2044.10 | 1128.21 |
| Total sedentary hours | 42.52 | 658.87 | 33.10 | 0.07 | .949 | -1297.82 | 1382.86 |
| Level of Stress | 903.17 | 773.10 | 47.69 | 1.17 | .249 | -651.52 | 2457.87 |
| Number of checked Fitbit data via Device | 629.56 | 469.27 | 29.75 | 1.34 | .190 | -329.16 | 1588.29 |
| Number of checked Fitbit data via App | -123.39 | 788.11 | 41.44 | -0.16 | .876 | -1714.51 | 1467.73 |
| Number of checked Fitbit data via PC/Web | -2306.03 | 2477.54 | 31.21 | -0.93 | .359 | -7357.61 | 2745.55 |

*p<0.05, **p<0.01

4) The effect of **evening** EMA independent variable on ***all of the activity level*** **(lightly/fairly/very)**of the day

This section describes the interaction with *total active minutes* as dependent variables and evening EMA as independent variables. During an evening EMA survey, the answer to the question of *"Did you share data or compete with your Fitbit friends via Fitbit app today? (answer choices: Yes/No)*" had a statistically significant interaction with the total of active minutes of the day. It appeared to positively interaction with

133.89 minutes. The result in regards to whether the participant had checked Fitbit data showed that it had a statistically significant interaction with total active minutes of the day. As the number of times that he or she had checked the data increased, there was a positive interaction with 24.65 minutes on *total active minutes*.

**Table 4.19 Relationship between Evening EMA Independent Variables and All of the Activity Levels**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | 98.71 | 122.28 | 39.62 | 0.81 | .424 | -148.49 | 345.91 |
| [Left the office=Yes] | 9.01 | 21.12 | 30.59 | 0.43 | .684 | -34.09 | 52.12 |
| [Mood state: Good] | 6.96 | 27.19 | 35.06 | 0.26 | .799 | -48.23 | 62.15 |
| [Mood state: Joyful] | 12.71 | 28.58 | 39.59 | 0.45 | .659 | -45.06 | 70.49 |
| [Mood state: Nervous] | 14.68 | 52.40 | 21.91 | 0.28 | .782 | -94.02 | 123.38 |
| [Mood state: Tired] | -9.69 | 25.50 | 23.22 | -0.38 | .707 | -62.41 | 43.03 |
| [Mood state: Depressed] | -143.65 | 109.02 | 28.16 | -1.32 | .198 | -366.91 | 79.61 |
| [Mood state: Annoyed] | -52.97 | 48.72 | 37.36 | -1.09 | .284 | -151.64 | 45.71 |
| [Mood state: Upset] | -34.29 | 116.04 | 13.36 | -0.30 | .772 | -284.31 | 215.73 |
| [Mood state: Other] | 71.72 | 100.01 | 21.66 | 0.72 | .481 | -135.88 | 279.32 |
| [Competed using Fitbit app =Yes] | 133.89 | 26.90 | 32.95 | 4.98 | .000** | 79.15 | 188.62 |
| [Physical activity level: Very Light] | 4.17 | 37.95 | 24.84 | 0.11 | .913 | -74.03 | 82.36 |
| [Physical activity level: Light] | 47.61 | 29.97 | 41.69 | 1.59 | .120 | -12.88 | 108.11 |
| [Physical activity level: Light Plus] | -18.19 | 24.60 | 35.31 | -0.74 | .465 | -68.11 | 31.73 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Physical activity level: Moderately Vigorous] | 80.15 | 46.31 | 25.56 | 1.73 | .096 | -15.11 | 175.42 |
| [Physical activity level: Moderately Vigorous Plus] | -31.82 | 69.52 | 28.12 | -0.46 | .651 | -174.20 | 110.55 |
| [Physical activity level: Vigorous] | 15.00 | 56.22 | 41.39 | 0.27 | .791 | -98.51 | 128.51 |
| [Physical Activity: Walking to the office when commuting] | -26.84 | 28.31 | 32.53 | -0.95 | .350 | -84.46 | 30.77 |
| [Physical Activity: Go to the gym to work out] | -46.62 | 58.34 | 47.49 | -0.80 | .428 | -163.95 | 70.71 |
| [Physical Activity: Use stairs instead of elevators] | -30.62 | 27.34 | 38.00 | -1.12 | .270 | -85.96 | 24.73 |
| [Physical Activity: Take a walk in the company] | -13.88 | 25.24 | 36.34 | -0.55 | .586 | -65.06 | 37.30 |
| [Physical Activity: Other (e.g., riding bicycle)] | 50.62 | 40.44 | 21.86 | 1.25 | .224 | -33.29 | 134.53 |
| Total working hours | -0.24 | 13.04 | 30.33 | -0.02 | .986 | -26.85 | 26.38 |
| Total sedentary hours | -16.59 | 10.89 | 33.06 | -1.52 | .137 | -38.75 | 5.57 |
| Level of Stress | 16.18 | 13.19 | 45.05 | 1.23 | .227 | -10.40 | 42.75 |
| Number of checked Fitbit data via Device | 24.65 | 7.82 | 24.97 | 3.15 | .004 | 8.55 | 40.75 |
| Number of checked Fitbit data via App | -11.93 | 13.83 | 44.86 | -0.86 | .393 | -39.79 | 15.92 |
| Number of checked Fitbit data via PC/Web | -17.52 | 44.11 | 36.27 | -0.40 | .694 | -106.95 | 71.91 |

*p<0.05, **p<0.01

4.1) The effect of evening EMA independent variables on *activities-minutes Lightly Active* of the day

During an evening EMA survey, the answer to the question of *"Did you s compete with your Fitbit friends via Fitbit app today? (answer choices: Yes/No)*" had a statistically significant interaction with activities-minutes Lightly Active per day. When participants reported that they did compete via Fitbit app, there was a positive interaction with 85.266 minutes on activities-minutes Lightly Active. The results regarding whether participants had checked Fitbit data for the day (question was “How many times have you checked your data via Fitbit device display today?”) showed that checking the devices’ data had a statistically significant interaction with activities-minutes Lightly Active. As the number of times that participants checked their data via Fitbit device display increased, there was a positive interaction of 20.889 ($p < 0.05$) on minutes lightly active throughout the day.

**Table 4.20 Relationship between Evening EMA Independent Variables and Activities-Minutes Lightly Active**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | 53.49 | 104.32 | 38.74 | 0.51 | .611 | -157.56 | 264.55 |
| [Left the office=Yes] | 7.58 | 18.46 | 39.61 | 0.41 | .684 | -29.75 | 44.91 |
| [Mood state: Good] | 19.31 | 23.48 | 44.41 | 0.82 | .415 | -27.99 | 66.61 |
| [Mood state: Joyful] | 3.58 | 23.85 | 43.56 | 0.15 | .882 | -44.51 | 51.66 |
| [Mood state: Nervous] | -2.78 | 45.61 | 23.80 | -0.06 | .952 | -96.96 | 91.39 |
| [Mood state: Tired] | -5.58 | 22.84 | 32.27 | -0.24 | .809 | -52.08 | 40.93 |
| [Mood state: Depressed] | -29.98 | 79.78 | 24.23 | -0.38 | .710 | -194.55 | 134.60 |
| [Mood state: Annoyed] | -13.93 | 41.99 | 42.63 | -0.33 | .742 | -98.63 | 70.78 |
| [Mood state: Upset] | -58.32 | 88.43 | 12.97 | -0.66 | .521 | -249.41 | 132.76 |
| [Mood state: Other] | 39.30 | 88.29 | 22.48 | 0.45 | .660 | -143.58 | 222.18 |
| [Competed using Fitbit app =Yes] | 85.27 | 23.33 | 39.81 | 3.65 | .001** | 38.10 | 132.43 |
| [Physical activity level: Very Light] | 20.59 | 33.71 | 31.90 | 0.61 | .546 | -48.09 | 89.27 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Physical activity level: Light] | 23.77 | 25.35 | 43.06 | 0.94 | .354 | -27.35 | 74.89 |
| [Physical activity level: Light Plus] | -13.42 | 21.03 | 40.03 | -0.64 | .527 | -55.93 | 29.09 |
| [Physical activity level: Moderately Vigorous] | 31.19 | 41.38 | 32.32 | 0.75 | .456 | -53.06 | 115.44 |
| [Physical activity level: Moderately Vigorous Plus] | -36.32 | 61.98 | 34.61 | -0.59 | .562 | -162.20 | 89.57 |
| [Physical activity level: Vigorous] | 3.35 | 47.41 | 46.25 | 0.07 | .944 | -92.06 | 98.75 |
| [Physical Activity: Walking to the office when commuting] | -29.70 | 24.72 | 40.89 | -1.20 | .236 | -79.63 | 20.22 |
| [Physical Activity: Go to the gym to work out] | -50.78 | 46.05 | 46.13 | -1.10 | .276 | -143.47 | 41.92 |
| [Physical Activity: Use stairs instead of elevators] | -15.64 | 23.21 | 46.88 | -0.67 | .504 | -62.34 | 31.06 |
| [Physical Activity: Take a walk in the company] | 5.51 | 21.84 | 42.84 | 0.25 | .802 | -38.54 | 49.56 |
| [Physical Activity: Other (e.g., riding bicycle)] | 0.41 | 36.65 | 30.32 | 0.01 | .991 | -74.40 | 75.22 |
| Total working hours | 11.64 | 11.59 | 38.55 | 1.00 | .322 | -11.82 | 35.10 |
| Total sedentary hours | -14.63 | 9.48 | 40.50 | -1.54 | .130 | -33.78 | 4.51 |
| Level of Stress | 14.91 | 10.87 | 46.53 | 1.37 | .177 | -6.97 | 36.79 |
| Number of checked Fitbit data via Device | 20.89 | 6.97 | 39.61 | 3.00 | .005** | 6.80 | 34.98 |
| Number of checked Fitbit data via App | -10.21 | 11.48 | 49.18 | -0.89 | .378 | -33.28 | 12.85 |
| Number of checked Fitbit data via PC/Web | -0.02 | 35.21 | 29.05 | 0.00 | 1.000 | -72.02 | 71.99 |

*p<0.05, **p<0.01

4.2) The effect of evening EMA independent variable on *activities-minutes Fairly Active* of the day

In terms of mood states, *depression* significantly interaction with *activity-minutes Fairly Active* of the day. When depressed, there was a negative interaction of -73.181 on activities-minutes Fairly Active. Also, having competition had a statistically significant interaction with activities-minutes Fairly Active of the day. Competing had a positive interaction of 33.017 on activities-minutes Fairly Active. With regards to total working hours, it also had a statistically significant interaction on the activity-minutes Fairly Active. As the total working hours increased, the negatively interaction the activities-minutes Fairly Active by -12.457. In case of activity level, *Moderately Vigorous* (e.g., weight lifting, aerobics) had a statistically significant positive interaction with activities-minutes Fairly Active of the day. *Moderately Vigorous* was found to have a positive interaction of 48.77 on activities-minutes Fairly Active.

**Table 4.21 Relationship between Evening EMA Independent Variables and Activities-Minutes Fairly Active**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | 87.04 | 48.61 | 32.21 | 1.79 | .083 | -11.94 | 186.02 |
| [Left the office=Yes] | 0.52 | 8.13 | 27.08 | 0.06 | .950 | -16.17 | 17.21 |
| [Mood state: Good] | -8.16 | 9.40 | 19.57 | -0.87 | .396 | -27.80 | 11.48 |
| [Mood state: Joyful] | 6.88 | 8.23 | 12.24 | 0.84 | .419 | -11.01 | 24.78 |
| [Mood state: Nervous] | -7.76 | 16.25 | 18.38 | -0.48 | .638 | -41.86 | 26.33 |
| [Mood state: Tired] | -2.48 | 9.73 | 18.16 | -0.26 | .801 | -22.91 | 17.95 |
| [Mood state: Depressed] | -73.18 | 31.99 | 20.31 | -2.29 | .033* | -139.86 | -6.51 |
| [Mood state: Annoyed] | -27.89 | 17.64 | 19.53 | -1.58 | .130 | -64.73 | 8.95 |
| [Mood state: Upset] | 0.21 | 23.10 | 9.77 | 0.01 | .993 | -51.42 | 51.84 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Mood state: Other] | -25.36 | 40.16 | 16.00 | -0.63 | .537 | -110.50 | 59.79 |
| [Competed using Fitbit app =Yes] | 33.02 | 9.32 | 22.77 | 3.54 | .002** | 13.73 | 52.31 |
| [Physical activity level: Very Light] | 0.16 | 14.62 | 27.93 | 0.01 | .992 | -29.80 | 30.12 |
| [Physical activity level: Light] | 18.16 | 11.73 | 32.37 | 1.55 | .131 | -5.73 | 42.05 |
| [Physical activity level: Light Plus] | 1.90 | 8.85 | 25.09 | 0.21 | .832 | -16.32 | 20.11 |
| [Physical activity level: Moderately Vigorous] | 48.78 | 18.21 | 32.04 | 2.68 | .012* | 11.69 | 85.86 |
| [Physical activity level: Moderately Vigorous Plus] | -44.22 | 27.33 | 27.70 | -1.62 | .117 | -100.23 | -44.22 |
| [Physical activity level: Vigorous] | -3.87 | 21.97 | 43.32 | -0.18 | .861 | -48.17 | 40.43 |
| [Physical Activity: Walking to the office when commuting] | -30.29 | 11.55 | 38.84 | -2.62 | .312 | -53.66 | -6.91 |
| [Physical Activity: Go to the gym to work out] | -3.17 | 21.15 | 38.50 | -0.15 | .882 | -45.97 | 39.62 |
| [Physical Activity: Use stairs instead of elevators] | -9.56 | 9.78 | 21.19 | -0.98 | .340 | -29.89 | 10.77 |
| [Physical Activity: Take a walk in the company] | -26.76 | 9.41 | 24.49 | -2.85 | .129 | -46.16 | -7.36 |
| [Physical Activity: Other (e.g., riding bicycle)] | 26.35 | 16.14 | 33.26 | 1.63 | .112 | -6.48 | 59.19 |
| Total working hours | -12.46 | 5.52 | 39.89 | -2.26 | .030* | -23.61 | -1.30 |
| Total sedentary hours | 1.65 | 4.18 | 26.65 | 0.40 | .696 | -6.93 | 10.24 |
| Level of Stress | 7.67 | 4.56 | 23.30 | 1.68 | .106 | -1.75 | 17.08 |
| Number of checked Fitbit data via Device | -0.28 | 2.96 | 27.10 | -0.09 | .926 | -6.34 | 5.79 |
| Number of checked Fitbit data via App | -2.01 | 4.58 | 23.43 | -0.44 | .665 | -11.46 | 7.45 |
| Number of checked Fitbit data via PC/Web | -26.37 | 18.74 | 35.49 | -1.41 | .168 | -64.39 | 11.64 |

*p<0.05, **p<0.01

4.3) The effect of evening EMA independent variable on *activities-minutes Very Active* of the day

In case of activity level, *Vigorous* (e.g., hiking, skiing, jogging) had a statistically significant positive interaction with activities-minutes Very Active in the afternoon. *Vigorous* was found to have a positive interaction of 35.622 minutes on activities-minutes Very Active. This shows that *Vigorous* is categorised as the strongest physical activity by MET and it actually matches to what people report in the surveys.

**Table 4.22 Relationship between Evening EMA Independent Variables and Activities-Minutes Very Active**

| Parameter | Estimated value | Standard error | df | t | P | 95% confidence interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower limit | Upper limit |
| intercept | -1.57 | 35.81 | 39.04 | -0.04 | .965 | -74.00 | 70.87 |
| [Left the office=Yes] | 5.97 | 6.54 | 24.66 | 0.91 | .370 | -7.51 | 19.44 |
| [Mood state: Good] | -1.59 | 8.17 | 29.21 | -0.20 | .847 | -18.30 | 15.12 |
| [Mood state: Joyful] | 0.05 | 8.45 | 30.18 | 0.01 | .995 | -17.20 | 17.30 |
| [Mood state: Nervous] | 7.36 | 13.82 | 6.74 | 0.53 | .612 | -25.59 | 40.31 |
| [Mood state: Tired] | 3.27 | 8.92 | 29.56 | 0.37 | .717 | -14.97 | 21.51 |
| [Mood state: Depressed] | -59.01 | 37.53 | 23.24 | -1.57 | .129 | -136.60 | 18.58 |
| [Mood state: Annoyed] | -22.07 | 14.58 | 23.18 | -1.51 | .144 | -52.22 | 8.08 |
| [Mood state: Upset] | 42.01 | 45.60 | 12.47 | 0.92 | .374 | -56.93 | 140.96 |
| [Mood state: Other] | 38.17 | 23.58 | 9.83 | 1.62 | .137 | -14.48 | 90.83 |
| [Competed using Fitbit app =Yes] | 15.22 | 8.12 | 26.30 | 1.87 | .072 | -1.46 | 31.90 |
| [Physical activity level: Very Light] | -22.78 | 13.22 | 27.24 | -1.72 | .096 | -49.90 | 4.34 |
| [Physical activity level: Light] | 4.37 | 8.17 | 10.86 | 0.53 | .604 | -13.64 | 22.38 |
| [Physical activity level: Light Plus] | -0.80 | 7.27 | 28.99 | -0.11 | .913 | -15.67 | 14.06 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| [Physical activity level: Moderately Vigorous] | 19.17 | 15.51 | 28.68 | 1.24 | .227 | -12.57 | 50.90 |
| [Physical activity level: Moderately Vigorous Plus] | 27.70 | 24.83 | 27.64 | 1.12 | .274 | -23.20 | 78.60 |
| [Physical activity level: Vigorous] | 35.62 | 17.39 | 38.02 | 2.05 | .047* | 0.42 | 70.83 |
| [Physical Activity: Walking to the office when commuting] | 18.73 | 8.01 | 13.76 | 2.34 | .135 | 1.52 | 35.95 |
| [Physical Activity: Go to the gym to work out] | 12.21 | 18.57 | 48.62 | 0.66 | .514 | -25.11 | 49.54 |
| [Physical Activity: Use stairs instead of elevators] | 4.39 | 7.91 | 26.85 | 0.55 | .584 | -11.86 | 20.63 |
| [Physical Activity: Take a walk in the company] | 6.18 | 7.17 | 10.96 | 0.86 | .408 | -9.61 | 21.97 |
| [Physical Activity: Other (e.g., riding bicycle)] | 4.64 | 14.24 | 31.17 | 0.33 | .747 | -24.40 | 33.69 |
| Total working hours | -2.79 | 3.83 | 19.79 | -0.73 | .475 | -10.79 | 5.21 |
| Total sedentary hours | 2.86 | 2.92 | 12.89 | 0.98 | .345 | -3.45 | 9.17 |
| Level of Stress | -4.94 | 3.57 | 17.66 | -1.38 | .184 | -12.46 | 2.57 |
| Number of checked Fitbit data via Device | 0.93 | 2.30 | 14.61 | 0.40 | .693 | -3.99 | 5.84 |
| Number of checked Fitbit data via App | 5.86 | 4.06 | 29.63 | 1.44 | .160 | -2.44 | 14.16 |
| Number of checked Fitbit data via PC/Web | -17.75 | 14.18 | 37.00 | -1.25 | .219 | -46.47 | 10.98 |

*p<0.05, **p<0.01

**Table 4.23 Summary of relation between EMA Morning and Evening as Independent Variables and Fitbit Data of the Day as Dependant variables: Analysis of Fitbit Data for the Day and EMA data**

| Dependent Variables | Independent Variables |
|---|---|
| *1. Steps of the **Day** provided by Fitbit* | **Morning EMA**<br>[**Morning** Feelings checked data: Motivated] **Positive**<br><br>**Evening EMA**<br>[**Today** Competed using Fitbit app] **Positive**<br>[**Evening** Activity level: Moderately Vigorous] **Positive** |
| ***2.** Minutes of All of the activity levels (Lightly, Fairly, Very) of the **Day** provided by Fitbit* | **Morning EMA**<br>[**Morning** Feelings checked data: Motivated] **Positive**<br><br>**Evening EMA**<br>[**Today** Competed using Fitbit app] **Positive**<br>[**Today** Number of checked Fitbit data via Device] **Positive** |
| ***2.1** Activities-Minutes Lightly Active of the **Day** provided by Fitbit* | **Morning EMA**<br>[**Morning** Feelings checked data: Motivated] **Positive**<br><br>**Evening EMA**<br>[**Today** Competed using Fitbit app] **Positive**<br>[**Today** Number of checked Fitbit data via Device] **Positive** |
| ***2.2** Activities-Minutes Fairly Active of the **Day** provided by Fitbit* | **Morning EMA**<br>[**Morning** Level of Stress] **Negative**<br>[**Morning** Feelings checked data: Motivated] **Positive**<br><br>**Evening EMA**<br>[**Evening:** Mood state: Depression] **Negative**<br>[**Today:** Competed using Fitbit app] **Positive**<br>[**Today:** Total Working Hours of the day] **Negative**<br>[**Evening:** Activity Level: Moderately Vigorous] **Positive** |
| ***2.3** Activities-Minutes Very Active of the **Day** provided by Fitbit* | **Morning EMA**<br>[**Morning:** Number of checked Fitbit data] **Positive**<br><br>**Evening EMA**<br>[**Evening:** Activity Level: Vigorous] **Positive** |

### 4.3 Phase 2: Demographics and Characteristics of Abandoners

This chapter describes the demographics (see Table 4.24) of sixty-six sample populations (n=66) forty-seven males (n=47) and nineteen females (n=19)) who had experiences using the devices but had stopped using them and were reselling their devices on an online secondary market. All sixty-six of the participants were recruited from an online secondary market, Naver Joonggonara, the largest online flea market in Korea.

#### 4.3.1 Demographic Descriptions

**Demographic Descriptions of Abandoners (see Table 4.24)**

The age of the sample population ranged from 19 to 39, with the highest number of participants from 30 to 34 years of age (n=25, 37.88%). All participants described themselves as office workers. Among them, sixteen (25.81%) participants were working at an Information Technology (IT) company. Ten participants (16.13%) reported they were working for the education field. Seven participants (11.29%) reported they were working in a manufacturing company, and five participants (8.06%) reported they were working in marketing. Other fields of work reported by the participants included finance, architecture, medicine, design, and aviation. Twenty-nine (n=29) participants (43.94%) had worked within a range of 1 to 4 years, and sixteen (24.24%) participants reported they had worked within a range of 5 to 9 years. Fourteen participants (21.21%) reported they had worked less than 1 year. The majority (n=61, 92.42%) reported they typically work more than 40 hours per week. Over half (n=34, 51.51%) indicated they work more than 46 hours. The majority (n=41, 73.21%) reported they usually get stressed at work.

**Table 4.24 Demographics of Phase 2 (Abandoners) Survey Study Participants (n=66)**

| Participant Demographics | Frequency | Percentage Frequency (%) |
|---|---|---|
| *Gender* | | |
| Male | 47 | 71.21 |
| Female | 19 | 28.79 |
| *Age* | | |
| 19 - 24 | 6 | 9.09 |
| 25 - 29 | 16 | 24.24 |
| 30 - 34 | 25 | 37.88 |
| 35 - 39 | 19 | 28.79 |
| 40 - 44 | 0 | 0 |
| 45 - 49 | 0 | 0 |
| 50 and over | 0 | 0 |
| *Years of Employment* | | |
| Less than 1 year | 14 | 21.21 |
| 1 - 4 years | 29 | 43.94 |
| 5 - 9 years | 16 | 24.24 |
| 10-14 years | 6 | 9.09 |
| More than 15 years | 1 | 1.52 |
| *Field of Work* | | |
| Finance | 4 | 6.45 |
| Information Technology (IT) | 16 | 25.81 |
| Medicine | 3 | 4.84 |
| Education | 10 | 16.13 |
| Manufacturing | 7 | 11.29 |
| Marketing | 5 | 8.06 |
| Architecture | 4 | 6.45 |
| Other | 13 | 20.97 |
| *Working Hours in a Week* | | |
| Less than 40 hours | 5 | 7.58 |
| 40 - 45 | 27 | 40.91 |
| 46 - 50 | 19 | 28.79 |
| 51 - 55 | 5 | 7.58 |
| 56 - 60 | 7 | 10.61 |
| 61 - 70 | 2 | 3.03 |
| More than 70 hours | 1 | 1.52 |
| Stress Level at Work * | | |
| Not at all (1) | 2 | 3.57 |
| Least stressed (2) | 13 | 23.21 |
| Somewhat stressed (3) | 19 | 33.93 |
| Extremely stressed (4) | 20 | 35.71 |
| Most stressed (5) | 2 | 3.57 |

*Likert Scale (1: Not at all, 5: Most stressed)

### 4.3.2 Physical Activity Related Description (see Table 4.25)

Similar to adopters, abandoners (n=66) were asked to report their physical activity (PA) status, including the amount of exercise per day, favorite types of PA level, PA that they typically perform while at work (opportunity for PA), and readiness to change PA when they first started using a wearable activity tracker. Twenty-four participants (36.36%) described being physically active on a daily basis (walking, running, working out) from 30 minutes to less than 1 hour, and 20 participants reported that they are usually physically active from 15 minutes to less than 30 minutes per day. Eighteen (27.27%) and nine participants reported that their favorite types of PA are Light (e.g., walking at a slow pace) and Light Plus (e.g., walking downstairs, cooking, shopping), respectively. Twelve (18.18%) and fifteen (22.73%) participants described that their favorite types of PA are Moderately Vigorous (e.g., weight lifting, aerobics) and Moderately Vigorous Plus (e.g., hiking, skiing). The participants performed PA to increase their PA level (step counts) while working in their everyday lives, as follows (the top 4 are): 1) Take a walk within the company (25.21%); 2) walk to the office when commuting (23.53%); 3) go to the gym to work out (21.01%); and 4) use stairs instead of the elevator (19.33%). Similar to the adopter questions, I also asked about abandoners' readiness to change their PA when they first started using the device. Unlike the adopter results, there were two participants who described themselves as belonging to the pre-contemplation stage, which represents "I am not physically active, and I don't plan on doing any physical activity in the near future." Nineteen participants (28.79%) described themselves as belonging to the contemplation stage; also, sixteen (24.24%) belonged to the preparation stage, thirteen (19.70%) to the action stage, and sixteen (24.24%) to the maintenance stage. The majority of participants (n=64, 96.97%) at least had the mindset and willingness to change their PA when they first started using the device.

**Table 4.25 Descriptive Statistics for Physical Activity Questions of Abandoners**

| Physical Activity Questions | Frequency | Percentage Frequency (%) |
|---|---|---|
| *Physical Activity (walking, running, working out) each day* | | |
| Less than 15 min | 5 | 7.58 |
| 15 mins - less than 30 mins | 20 | 30.30 |
| 30 mins - less than 1 hr | 24 | 36.36 |
| 1 hr - less than 2 hrs | 15 | 22.73 |
| 2 hrs - less than 3 hrs | 1 | 1.52 |
| More than 3 hrs | 1 | 1.52 |
| *Favorite type of Physical Activity* | | |
| Very Light | 9 | 13.64 |
| Light | 18 | 27.27 |
| Light Plus | 9 | 13.64 |
| Moderately Vigorous | 12 | 18.18 |
| Moderately Vigorous Plus | 15 | 22.73 |
| Vigorous | 3 | 4.55 |
| *Physical activities that typically perform while work** | | |
| Walk to the office when commuting | 28 | 23.53 |
| Go to the gym to workout | 25 | 21.01 |
| Use stairs instead of elevators | 23 | 19.33 |
| Participate in exercise programs at work | 5 | 4.20 |
| Take a walk in the company | 30 | 25.21 |
| Workout personally after work | 5 | 4.20 |
| Other | 3 | 2.52 |
| *Readiness to change physical activity when first started using the device* | | |
| Pre-contemplation | 2 | 3.03 |
| Contemplation | 19 | 28.79 |
| Preparation | 16 | 24.24 |
| Action | 13 | 19.70 |
| Maintenance | 16 | 24.24 |

* Multiple selections possible

### 4.3.3 Wearable Activity Tracker-Related Description (see Table 4.26)

I asked participants what kinds of wearable activity trackers they are selling in the secondary market, and the results included the following: 1) Fitbit (n=41, 62.12%); 2) Samsung Gear Fit (n=17, 25.76%); 3) Xiaomi Mi Band (n=6, 9.09%); and Zikto Walk (n=2, 3.03%). The range of the device usage period varied, in that nine participants reported they used their device less than 1 month (n=9, 13.64%), eleven participants used the device from 1 month to 3 months (n=11, 16.67%), fifteen participants reported they used the device from 3 months to 6 months (n=15, 22.73%), sixteen participants reported they used the device from 6 months to less than 1 year (n=16, 24.24%), twelve participants used the device from more than 1 year to less than 2 years, and three participants reported they used the device more than 2 years (n=3, 4.55%). While using the device, steps (34.62%) data were measured the most by participants, followed by sleep (21.15%), heart rate (17.95%), calories (14.10%), and distance (11.54%).

The majority of participants (n=50 out of 66, 75.76%) purchased the device personally through their own intention, twelve participants (18.18%) received the device as a gift, and two participants received the device through the company via an exercise program. Most of the abandoners (n=58, 87.88%) used the device every day before selling it on the online secondary market. For the abandoners, the device was mainly used for tracking PA (n=56, 40.88%) and as a clock or alarm (n=29, 21.17%).

**Table 4.26 Descriptive Statistics for Wearable Activity Trackers Questions of Abandoner**

| Wearable Activity Trackers Questions | Frequency | Percentage Frequency (%) |
|---|---|---|
| *Kind of Wearable Activity Tracker Selling in the Secondary Market* | | |
| Fitbit | 41 | 62.12 |
| Samsung Gear Fit | 17 | 25.76 |
| Xiaomi Mi Band | 6 | 9.09 |
| Zikto Walk | 2 | 3.03 |
| *Kind of Any Wearable Activity Tracker Used in the Past** | | |
| Fitbit | 41 | 47.67 |
| Samsung Gear Fit | 18 | 20.93 |
| Xiaomi Mi Band | 15 | 17.44 |
| Jawbone Up | 1 | 1.16 |
| Garmin VivoFit | 1 | 1.16 |
| Nike FuelBand | 2 | 2.33 |
| Shine | 1 | 1.16 |
| Basis | 0 | 0 |
| Other | 7 | 8.14 |
| *Device Usage Period* | | |
| Less than 1 week | 2 | 3.03 |
| More than 1 week - Less than 1 month | 7 | 10.61 |
| More than 1 month - Less than 3 months | 11 | 16.67 |
| More than 3 months - Less than 6 months | 15 | 22.73 |
| More than 6 month - Less than 1 year | 16 | 24.24 |
| More than 1 year- Less than 2 years | 12 | 18.18 |
| More than 2 years | 3 | 4.55 |
| *Biometric data that measured with the device** | | |
| Steps | 54 | 34.62 |
| Heart Rate | 28 | 17.95 |
| Distance | 18 | 11.54 |
| Calories | 22 | 14.10 |
| Sleep | 33 | 21.15 |
| Other | 1 | 0.64 |

| | | |
|---|---|---|
| *How did you first get the device you used?* | | |
| Made purchase personally | 50 | 75.76 |
| Received as a gift | 12 | 18.18 |
| Won at an event | 1 | 1.52 |
| Received from the company (via an exercise program) | 1 | 1.52 |
| Other | 2 | 3.03 |
| *How often did you wear (use) the device you used?* | | |
| Everyday | 58 | 87.88 |
| Once a week | 6 | 9.09 |
| Once a Month | 0 | 0 |
| Once or Twice per year | 0 | 0 |
| Other | 2 | 3.03 |
| *Which of the features did you mainly use when using the device?** | | |
| Tracking physical activity | 56 | 40.88 |
| Viewing the data provided by device via a website or mobile | 21 | 15.33 |
| Competing with friends who are registered on the device | 7 | 5.11 |
| Sharing health data on SNS | 2 | 1.46 |
| Setting own goals | 22 | 16.06 |
| As a Clock or alarm | 29 | 21.17 |

* Multiple selections possible

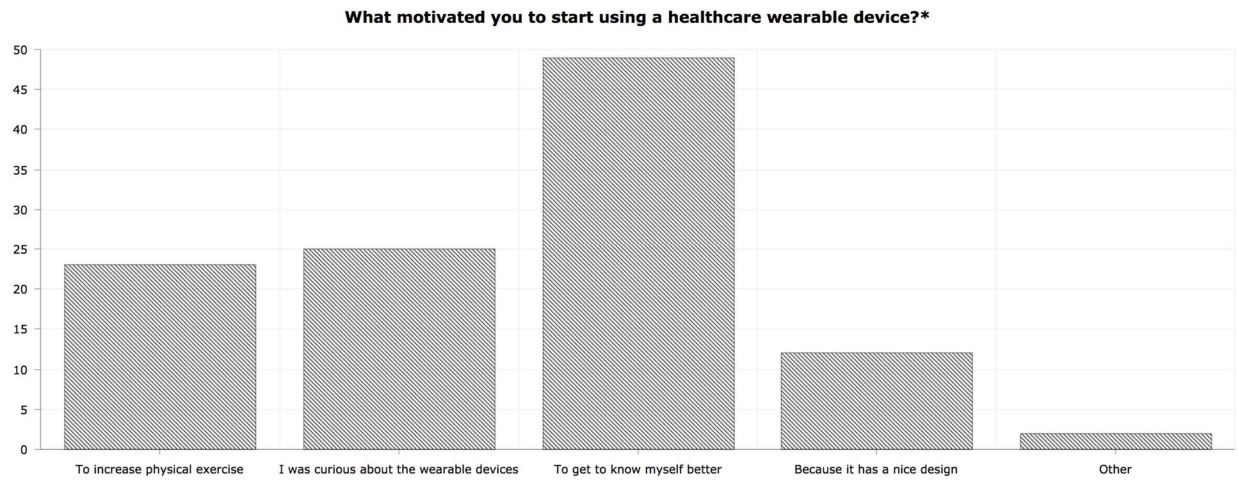
### 4.3.4 Motivation to Start Using a Wearable Activity Tracker

To examine whether there was a differences in motivation to start using the device between adopters and abandoners, I also asked abandoners what motivated them to start using a wearable device. As shown in Figure 4.1, the most common reason was “to get to know myself better by using the device” (41.53%), followed by “I was curious about the wearable device” (21.19%) and “to increase the amount of physical exercise” (19.49%). P58 (who was selling the Fitbit Alta with a green color) reported that he/she started using the device to get to know his/her data:

> *The reason I started using the device was that I was curious about my own data, as I work out regularly. Especially, I thought checking heart rate would allow me to see the average condition. The statistics can show in what circumstances would the heart rate increase, so I wanted to use such functions. (P58)*

When starting to use the device, the motivation was similar among adopters and abandoners. Although the motivation for using the device was very similar among the two populations, why the abandoners stopped using the device after some period of time will be covered in the next section.

**Figure 4.1 Answers for "What motivated you to start using a healthcare wearable device?" (Multiple selections allowed)**



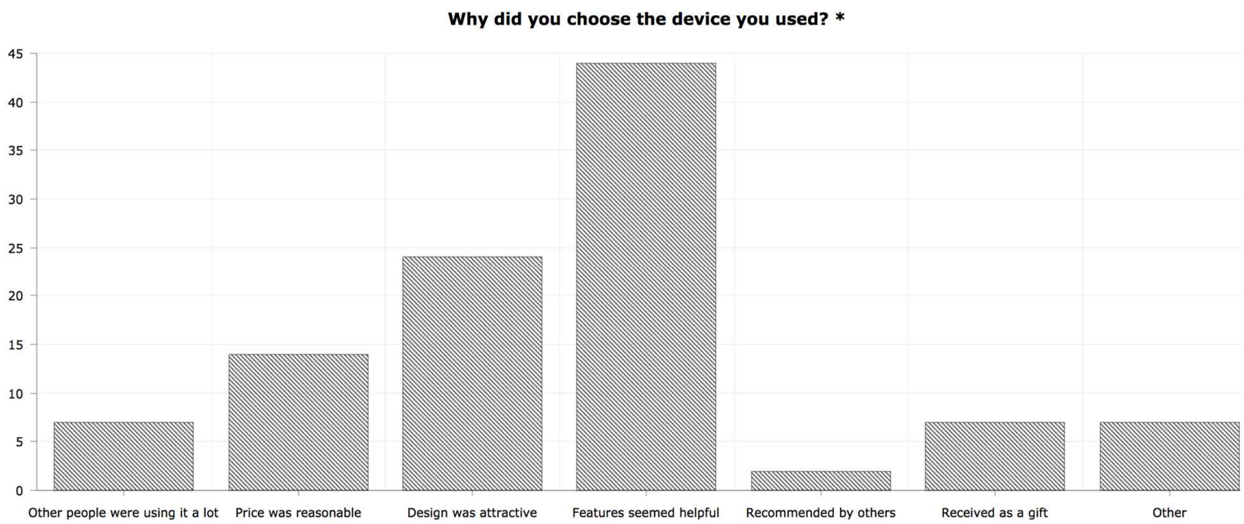

| Answer | Frequency | Percentage Frequency |
|---|---|---|
| To increase the amount of physical exercise | 23 | 19.49 |
| I was curious about the wearable devices | 25 | 21.19 |
| To get to know myself better | 49 | 41.53 |
| Because it has a nice design | 12 | 10.17 |
| Other | 2 | 1.69 |

### 4.3.5 Reasons for Choosing the Device They Used

I explored why the participants chose a specific device among others. The biggest reason was that the "features seemed helpful" (41.90%), in that they liked the function provided by the device. P54 (who was selling the Fitbit Charge 2) reported that he/she chose the Fitbit Charge because Fitbit provided a weekly progress summary report, which looked really helpful. But P54 stopped using it since she/he was not interested in exercise anymore because there was no time to exercise as an office worker.

*I chose this health device among many others because I was told that its weekly progress health report would systematically inform me of my status. In fact, Fitbit summarizes and shows the basic information (weekly steps, calories, etc.) every week, and it was so helpful that I even thought of purchasing the paying service that provides more detailed information. Now that I am an office worker, it's hard to find spare time [for exercise] and I lost interest in exercising, so I no longer use the device. (P54)*

**Figure 4.2 Answers for "Why did you choose the device you used?" (*Multiple selections allowed)**




| Answer | Frequency | Percentage Frequencey |
|---|---|---|
| Other people were using it a lot | 7 | 6.67 |
| Price was reasonable | 14 | 13.33 |
| Design was attractive | 24 | 22.86 |
| Features seemed helpful | 44 | 41.90 |
| Recommended by others | 2 | 1.90 |
| Received as a gift | 7 | 6.67 |
| Other | 7 | 6.67 |

### 4.3.6 Reason for Abandonment (Table 4.27)

To better understand why participants abandoned and no longer used their device, and to explore their experience after discontinuing use, I asked why they abandoned and sold their device and if there were any emotional changes once they stopped using the device. One of the biggest reasons participants stopped using the device was that “it was uncomfortable to use the device due to the design aspects and functionality” (29.07%). During a 5-minute exit interview, P15 (who was selling the Fitbit Blaze with a black color) stated that he/she did not like the user interface (UI) design and functionality, which is why he/she stopped using the device:

> *UI design is not my style. It is good to wear casually everyday, but it does not suit the clothes that make up a little formalism. Also, the heart rate and calories were not accurately measured, so it was just like a simple pedometer and not a smart health tracker.* (P15)

The second most selected reason for abandoning the device was “I kept forgetting to wear it every day” (17.44%), followed by “to purchase a new device” (15.12%), “The measurement for physical activity is not useful” (9.30%), and “The information provided by the device is not useful” (9.30%).

P28 (who was selling the Fitbit Charge 2 with a blue color) reported that he/she bought a Fitbit device due to his curiosity about the technology, and after the curiosity (novelty) wore off, it no longer interested him/her. Also, P28 asserted that since the steps and heart rate data were very similar in pattern every day, the information provided by the device was no longer useful:

> *Participant (28): It was because of curiosity that I bought Fitbit in the beginning, so I would say that since I got to know what it is, I am no longer interested in it. Indeed, I bought it for exercise, but all that I monitored were the heart rate and the number of steps, and there was no change in those data. They were showing mostly the same distance and not much difference, so I decided to sell it.*

*Participant (42): Measuring physical activity is no longer my concern. In the end, the data is the same every day. My pattern is the same while the data does not show anything different, it is not interesting anymore.*

Similarly, I asked the abandoners why they sold their device at a secondhand market. The most common reason was that participants wanted to buy a better device (29.90%), so they needed money to buy a new device. P51 (who was selling the Fitbit Charge 2 with a black color) described that she/he wanted to buy a smartwatch, such as the Samsung Galaxy Gear:

*Participant (P51): I am going to change to a better device. The function of wearable devices is important, but I think they should also act as accessories. So, I'm going to get Galaxy Gear. Interviewer (Me): Regarding the role of accessory, do you think Fitbit has weak design and you prefer Galaxy Gear's design?*

*Participant (P51): As well as the design, there are more features on Smart Watch that can work with mobile phones.*

P34 (who was selling the Mi Band 2) stated that she/he also wanted to buy a smartwatch such as the Apple iWatch. Unlike my research participants who were adopters and who liked the device's focus on PA in Phase 1 of the study, the abandoners in Phase 2 of the study were not satisfied with the fitness-oriented band; instead, they wanted a smartwatch that provided more functions than just activity trackers.

The second most selected reason for selling the device was "Its function fell short of my expectation" (19.59%). Several participants reported they were not satisfied with the accuracy of the measurement for PA, which is not useful:

*Interviewer (Me): You answered that the Fitbit falls short in terms of its function. Can you explain more in detail?*

*Participant (P32): I meant for its accuracy. For instance, If I play tennis, it reaches up to 10,000 steps too quickly. I also doubt that the calories are correct. It is at its best when you walk at a constant pace in straight posture. (P32 who were selling the Fitbit Charge 2 with black colour).*

P13 (who was selling the Mi Band 2) also stated that he/she was not satisfied with the device's accuracy of measurement:

*After I swam, what is measured was not accurate nor constant, so it did not help me so much. It's just waterproof and measured the time and calories. I bought this model because of waterproofing, but it does not mean anything. (P13)*

P43 (who was selling the Fitbit Charge HR with a purple color) complained that the waterproof function did not work well and that the battery did not last longer:

*It was not waterproof and the battery did not last long enough, so it was annoying to charge. The heart-rate sensor light was bothering too, and I decided to put normal watch because it is better in terms of design. (P43)*

During a survey and exit interview, I asked for participants to recount the emotional changes in their lives after abandonment. The survey results indicated that a majority of the participants' responses regarding their emotional changes once they stopped using the device were "no change" (80.30%) after abandonment, followed by "freedom" (10.61%). P31 stated that he/she felt more freedom and could concentrate more on his/her life by maintaining very simple tasks and interests after abandoning the device. P31 explained that he/she wanted to take on a more minimalistic life:

*Interviewer (Me): You mentioned that your concentration has improved since you abandoned the device. Could you explain a little more?*

*Participant (P31): Comfort and concentration. I think it is because it allows me to pay less attention. Now that the minimal life is a fad…*

*Interviewer (Me): Did the device not affect your workout?*

*Participant (P31): It does, but I think it actually is more effective when not in use. Rather than the motivations for me to exercise, what it provides in daily life was more attractive, like comfort and concentration.*

Interestingly, most of my abandoners (n=63 out of 66, 95.45%) who were selling their devices on the secondhand sales market stated they would use a wearable activity tracker again in the future. P42 stated that she/he would use the device later when she/he needed health management, but she/he did not need to manage his/her health at the moment.

**Table 4.27 Descriptive Statistics for Abandonment Questions**

| Participant Demographics | Frequency | Percentage Frequency (%) |
|---|---|---|
| *Why are you no longer using the device?** | | |
| It was uncomfortable to use (Design & Functions) | 25 | 29.07 |
| The device seemed not so helpful for exercise | 4 | 4.65 |
| I kept forgetting to wear it everyday | 15 | 17.44 |
| Its design is not appealing | 7 | 8.14 |
| The information provided by the device is not useful | 8 | 9.30 |
| The measurement for exercising (physical activity) is not accurate | 8 | 9.30 |
| It has too many features | 0 | 0 |
| For purchasing new device | 13 | 15.12 |
| Other | 6 | 6.98 |
| *Similarly, if you are now selling this device at a second-hand market, what is the reason?** | | |
| Measuring how much physical activity I do is no longer my concern | 16 | 16.49 |
| I developed a health problem | 3 | 3.09 |
| I already achieved my goal by using the device | 2 | 2.06 |
| Its functions fell short of my expectations | 19 | 19.59 |
| I have a similar device | 13 | 13.40 |
| Its size does not fit | 1 | 1.03 |
| Due to financial reasons | 8 | 8.25 |
| Made a wrong purchase or received a wrong gift | 0 | 0 |
| It is too complicated to use | 0 | 0 |
| To buy a better device | 29 | 29.90 |
| Due to changes in daily life (i.e., changed job) | 4 | 4.12 |
| Other | 2 | 2.06 |
| *Did you have any emotional changes once you stopped using the device? If so, what kind of emotional change would it be?* | | |
| No change | 53 | 80.30 |
| Frustration | 0 | 0 |
| Guilt | 2 | 3.03 |
| Freedom | 7 | 10.61 |
| Other | 4 | 6.06 |
| *Do you think you would use wearable activity tracker again in the future?* | | |
| Yes | 63 | 95.45 |
| No | 3 | 4.55 |

* Multiple selections possible

# CHAPTER 5. DISCUSSION

This chapter analyzes both qualitative research data from interview transcripts of 27 participants and all quantitative data, including the results of EMA analysis mentioned in the previous chapter. I used both inductive and deductive analysis methods to provide findings that demonstrate how the context of everyday life affects physical activity steps through the use of wearable devices. In Chapter 5.1, I described analysis of both qualitative research data and quantitative EMA data to explain individual contextual factors; so, how qualitative interview data supports quantitative EMA data (individual contextual factors). In this section, each significant factor is described with support by an interview quotation. In Chapter 5.2, I defined five elements by using deductive and inductive processes: environment, information and communications technology (ICT), contextual factors, information activities, and life activities. By using these five elements, in Chapter 5.3, I proposed a model based on analysis and findings of my research. In this chapter, I describe the critical themes, which support the model. In Section 5.4, I described how I was trying to answer the research questions in light of all the results.

## 5.1 EMA Analysis and Qualitative Interview Data

In this section, I will describe the contextual and environmental factors that showed statistical significance from EMA analysis (explained in chapter 4.2) through my research study. These statistically significant factors are summarized in Table 5.2 and Table 5.5. By employing qualitative interview data, I will try to understand the possible causal relationships between significant independent variables and dependent variables. There are differences between Table 5.2 and Table 5.5. The morning steps data and evening steps data, which were dependent variables used in Table 5.2, were reported by the research participants after checking step data on their Fitbit devices during morning and evening EMA surveys.

By asking them to provide morning and evening step data, I could discover which individual contextual and environmental factors interacted with the morning and evening numbers of steps.

On the other hand, the dependent variables used in Table 5.5 were total steps and total activity minutes of the day as collected through participants' Fitbit log data. The total steps and total activity minutes were calculated by end of the day and time-stamped in order to be aligned with the EMA survey. Through this method, I could see what contextual factors interacted with total steps and active minutes of the day.

In the morning and the evening EMAs, there was a section that asked similar types of questions (e.g., current mood, level of physical activity mainly done in the morning or evening respectively) and another section that asked different questions. During a morning EMA, questions consisted mainly of what participants did in the morning such as their current mood and levels of stress. On the other hand, during an evening EMA, questions consisted mainly of a summary of the day (e.g., today's total working hours and today's sedentary time) and also what participants did in the evening. To better understand the analysis of EMA results, which factor correlation with step counts, I created Table 5.1, which shows the types of questions that were asked during morning and evening EMAs based on the time scheduled.

**Table 5.1 Questions Asked During Morning and Evening EMAs and Used in EMA Analysis**

| Time | Action |
|---|---|
| 8:00 AM - 9:00 AM | **Morning EMA collected** |
| | **Morning Steps reported by user** |
| | **(*Total number of steps counted from 12:00 am to 9:00 am*)** |
| | Transportation regime |
| | Current mood state |
| | Current level of stress |
| | Number of checking Fitbit data in the morning |
| | Way for checking data (Fitbit device/mobile app/PC) |
| | Level of physical activity mainly done in the morning |
| | Physical activity performed on the way to work or at the office in the morning |
| | Feeling checked if data motivated |
| 12:00 PM - 1:00 PM | **Lunch Time** |
| 6:00 PM - 7:00 PM | **Evening EMA collected** |
| | **Evening Steps reported by users** |
| | **(*Total number of steps counted from 12:00 am to 7:00 pm*)** |
| | Whether left the office or not |
| | Current mood state |
| | Level of physical activity mainly done in the evening |
| | Today's working hours |
| | Today's sedentary time |
| | Today's level of stress |
| | Today's number of checked Fitbit data via Device |
| | Today's number of checked Fitbit data via App |
| | Today's number of checked Fitbit data via PC/Web |
| | Today's physical activity performed at the office |
| | Competing with Fitbit friends today |
| 11:59 PM | Steps of the Day collected through Fitbit data log |
| | **(*Total number of steps counted from 12:00 am to 11:59 pm*** |
| | Minutes of Total activity levels (Lightly, Fairly, Very) of the Day: Fitbit data log |

### 5.1.1 Relationship between EMA Morning and Evening Independent Variables and Morning and Evening Self-Reported Step Counts

The morning step data and evening step data, which were dependent variables used in Table 5.2, were reported by users after checking their step data on the Fitbit devices during morning and evening EMA surveys. I will explain each statistically significant factor, as in the more important results only in more detail with qualitative interviews in the following section.

#### 5.1.1.1 Relationship between Self-Reported Morning Steps and Morning EMA

1) [**Morning** Mood State: Tired**]** **Negative**

There is a negative correlation between a *Tired* morning mood state and morning number of steps. Previous studies also discussed that fatigue (tiredness) affects physical activity performance; fatigue could be related to shorter or less working out, which leads to reduced duration of exercise or level of activity (Belza, 1994). During a morning EMA survey, participants usually felt tired (31.9%), which was the second most chosen response in mood state in the mornings (Table 4.7). My qualitative interview data supports quantitative EMA analysis; during interviews, participants also stated that they do not want to do physical activities when they feel tired. Participant 26 stated that when she felt tired upon waking up in the morning, she skipped exercise:

> Participant 26: *I skipped exercise when I was tired when I woke up in the morning. My mood and physical status in the morning affected the momentum of my day.*

Interestingly, participant 11 also stated that when he exercised when he felt tired, it was similar to exercising after drinking a lot of alcohol the day before, so he hesitated to do more physical activity when he felt tired.

Participant 11: *Actually, my physical activity is influenced by my mood. When I feel tired, I do not want to exercise. If I exercise when I'm tired, it feels like I've drunk a lot the day before and am exercising in the morning.*

As with the above results, the mood state *Tired* and number of steps taken in the morning are closely related each other.

2) [**Morning** Mood State: Good] **Negative**

In morning EMAs, a good mood (34.6%) was the most selected response during the 5 days of EMA (Table 4.7). Among different mood states, *Good* has a negative statistically significant correlation with the number of steps taken in the morning. This means that in a *Good* mood, one would walk less by -842.30 number of steps ($p<0.01$) (see Table 4.7). This result is somewhat surprising because it shows the opposite of what is often believed in general: that one would walk more when he or she is in a good mood(Carels, Berger, & Darby, 2006). One explanation could be that many people desire to exercise more when they feel their bodies are stiff and not in very good condition. Participant 1 stated that he usually worked out in the morning when he felt his body was stiff and not very refreshed.

Participant 1: *In the mornings, when I wake up and I feel that my body is not in very good condition, I try to go to the gym in the morning at my company.*

3) [**Morning** Physical Activity Level: Very Light] **Negative**

Based on morning EMA data, one of the most frequent responses for level of physical activity participants reported is that they usually performed Very Light (40.8%) (e.g., reading, standing, talking, sitting in office, studying) levels of PA in the morning. Quantitative EMA analysis results indicated that participants reported they mainly did very light physical activity (sitting in the office) in the morning, and were found to walk less -1309.75 steps counted ($p<0.01$). During an interview, participant 4 reported that after she arrived at work, she had no time available to walk until lunch time, because she was sitting at her desk most of the time throughout the morning.

> Participant (P4): *Yes. I cannot leave work for home on time… As a matter of fact, I do not walk till lunchtime once I sit down at my desk in the morning. So, there is no time to walk.*

These results assume that sitting in an office has a significant interaction with reducing the number of steps in the morning. As previous research indicates this as well, I could suggest that breaking up sedentary time with short-term physical activity has a positive impact on health by reducing sitting time (Healy et al. 2011).

4) [**Morning** Physical Activity Level: Moderately Vigorous Plus] **Positive** and [**Morning** Physical Activity Level: Vigorous] **Positive**

Actually, during the morning, there are not that many participants who did Moderately Vigorous Plus (e.g., swimming, tennis, dancing, biking) (3.7%) or Vigorous activities (e.g., hiking, skiing, jogging) (1.4%) (see Table 4.7). Interestingly, even though only a few participants reported that they did strenuous workouts during the morning, the statistical results indicated that morning workout correlated with increased steps in the morning. When participants reported to the morning survey that they mainly did Very Light physical activity (sitting in the office) in the mornings, they were found to walk less by -1309.75 number of steps ($p<0.01$), while participants with a Moderately Vigorous Plus activity level walked more, by 9837.66 number of steps ($p<0.01$) (see Table 4.9). Those with Vigorous activity levels walked 7328.83 ($p<0.01$) number of steps more. Moderately Vigorous Plus and Vigorous levels of physical activity show around 10,000 more steps, which is a huge difference compared to Very Light physical activity.

During an interview, participant 4 reported that he usually goes to work by bicycle and works out at his company gym in the morning before going to work. He does not have time to work out after work, since he usually needs to work late nights and also has many dining obligations together with colleagues.

Furthermore, when he was active in the morning (whether moderate or vigorous), he tended to be more active and energetic during the day.

> Participant 4: *We have a gym at my company. So, I wake up and go to the gym at the company by bicycle and then work out for 30 minutes and go to work immediately. Usually, I do not have the opportunity to walk in the office. So, I prefer to work out in the morning, mainly because I work until late. Usually, we have a lot of meals (dinner) together at the company, so I do not have time to work out. Also, if I had exercised in the morning, I was more energized during the day.*

We could thus suggest that morning workouts before going to work may provide a better opportunity during the day among office workers who do not have time to work out.

#### 5.1.1.2 Relationship between Evening Steps and Evening EMA

1) [**Evening**: Left the office = Yes] **Positive**

During evening EMA interviews, I asked the participants whether they left their offices or not (Question: "*Did you leave work*?" answer options: 1) Yes, 2) No, and 3) I'm leaving now). The question was sent between 6:00 p.m. and 7:00 p.m. and collected before 9:00 p.m. If a respondent choose "Yes" for this question, he/she left the office before he/she submitted their response. Based on EMA statistical results, there is a correlation between leaving work early and taking more steps. It could be hypothesized that leaving work earlier (fewer hours in the work day) allows more time for other activities, including exercise. During evening EMA surveys, main activities right before the survey were queried (Q. "What were you doing right before the survey prompts?"), and the responses were as follows: computer work (25.2%); doing housework (cleaning, cooking, etc.) (18.5%); eating meals (12.6%); and working out/exercising (7.4%). During my qualitative interview, participant 4 mentioned that he preferred to work out after work.

Interviewer (Me): *In your survey response, you checked that you were mostly sitting and doing light activity during the day. How about physical activity? Do you usually exercise?*

Participant 4: *Yes, after work I am trying to do some exercise. In the survey, as I checked that I was sitting almost eight hours, there is almost no physical activity during my time at the company. So, I try to move a lot after leaving work. My step goal is 10,000 steps per day, so if I do not have a lot of activity and want to get 10,000 steps, I walk from transit to home or try to move a lot; this is how I filled up the number of steps.*

Thus, we could suggest that shorter work days may provide better opportunities for more exercise.

2) [**Evening** Mood State: Joyful] **Negative**

Among different mood states, *Joyful* has a negative statistically significant correlation with the number of steps taken in the evening. This means that in a *Joyful* mood, one would walk less by -2249.17 number of steps ($p<0.01$) (see Table 4.7). During morning EMAs, *Joyful* (13.6%) was the third most selected response during 5 days of EMA. One possible hypothesis is that people reporting this mood walk less because they are already happy. Many people desire to exercise more to relieve tension from work. Maybe these people don't need to relieve stress. During an interview, participant 6 reported that she got stressed and felt annoyed in the morning, but her mood improved at the end of her shift:

Interviewer (Me): *When I checked your response from the questionnaire ... In the evening surveys, when you left the company, or in the afternoon, you reported that you were in a good mood, but in the morning you often checked that you were in an annoyed mood. Do you have a pattern of getting stressed in the morning?*

Participant 6: *Yes, I usually get stressed before I start work in the morning. But I do not have a lot of thoughts while I work, and when I get to the end of the workday, I feel happy when I have a pleasant appointment or a pleasant occasion scheduled that evening.*

3) [**Evening** Physical Activity Level: Moderately Vigorous Plus] **Positive**

Similar to the morning questionnaire, I asked a question about what level of physical activity participants performed during the afternoons. Most participants reported that they usually performed a physical activity level of Very Light (41.1%) (e.g., reading, standing, talking, sitting in office) or Light (37.7%) (e.g., walking at a slow pace, light office work) (see Table 4.8). Qualitative interviewing also supports that participants usually spend sedentary time during work:

Interviewer (Me)*: Do you have time to stand up and have some break time during work?*

Participant (P9): *Typically, I spend my time in a sitting position. I stand up only when I go to the toilet or want to drink water.*

Even though most of participants reported that they spent most of their time sitting at work, Moderately Vigorous Plus activity level (e.g., swimming, tennis, dancing, biking) has a statistically significant correlation with the number of steps taken in the evening (more walking by 5861.87 number of steps). During an interview, participant 8 stated that he usually uses lunch time to go to the gym at his company.

Participant (P8): *Once a day, I run on the treadmill. If you go downstairs here, we have a gym in the basement at our company. Employees are able to exercise. So, I do work out, usually at lunch time.*

Interviewer (Me): *Oh, so you're going to the gym to work out both at lunchtime and after work*?

Participant (P8): Almost always at lunch, sometimes even in the evenings when I have no appointments.

Also, participant 19 stated that he uses lunchtime to walk more to try to achieve his Fitbit step goals:

*Participant (P19): What I do most often is, when commuting to work, I walk about 3km on my way to work instead of riding a bus, and come back home walking as well. I set my goal of reaching 10,000 steps a day, so I try to walk and achieve this while commuting. When I drive to work, I go out and walk during lunchtime. By doing so, I have been trying to achieve my goal.*

During work, participants usually sat at their company all day, but some of them used lunchtime to get some exercise time. We could suggest that exercise using lunch time could be helpful to increase physical momentum in the daily lives of office workers.

4) [**Today:** (**Daytime**) Physical Activity: Use stairs instead of elevators] **Positive** and [**Today:** (**Daytime**) Physical Activity: Other (e.g., riding bicycle)] **Positive**

During an evening EMA, I asked participants to report all physical activities that they did during the day. Answer options for the question were 1) Walk to the office when commuting (33%), 2) Go to the gym to work out (4.5%), 3) Use stairs instead of elevators (18.6%), 4) Participate in exercise programs at work (0.4%), 5) Take a walk in the workplace (37.9%), and 6) Other (5.6%) (Table 4.8). In terms of the physical activity that participants did during that day, [Using stairs instead of elevators] has a statistically significant correlation with the number of steps taken during that day (walked more by 1877.83 number of steps ($p<0.05$)). Based on interview data, office workers reported that they did not have time to work out during weekdays. The majority of people in the study worked for a long time until late at night, stating that they did not have time to exercise separately. Office workers tried to find ways to move a little more in their workplaces in daily life. Our office worker participants were looking for ways to walk more in everyday life. During an interview, participant 11 reported that when he check his Fitbit before or during lunch and realized that he still had a ways to go, he tried to take more stairs. Whenever he realized he was behind his daily step goal, he tried to increase his exercise by using stairs instead of elevators.

Interviewer (Me): *What do you do at work, besides time during breaks and lunch breaks? Walking around, or…*

Participants (P11): *I tend to use stairs instead of the elevator when going to other departments for a meeting or approval of something, which also counts as a little bit of exercise. When I check my Fitbit data before or during lunch and realize that I still have a lot of room before reaching my goal, I try to walk a lot and move a lot.*

Furthermore, on the question about physical activity in the evening, the answer of "*other*" (e.g., riding a bicycle) had a statistically significant correlation with the number of steps taken in the evening (average for the "other" group: 3555 steps; $p < 0.05$). Only 5.6% of the participants reported engaging in "other" physical activity during the day (from morning to until submitting the response). The "other" response included a blank for respondents to list the activities that they were doing. The responses mainly involved bicycle riding, working out, or playing badminton after work; they also included physical activities that increased the number of steps, such as shopping. This correlated with leaving work earlier (left the office = "yes") and thus with fewer hours in the work day, as leaving work allowed respondents more time for other activities, including exercise (5.1.1.2, section #1).

5) [Today: Competed Using Fitbit App] **Positive**

During an evening EMA, I asked participants whether they competed with their Fitbit friends during the day (Q. Did you compete with your Fitbit friends via Fitbit app today? Answer options: 1) Yes 2) No). Based on the descriptive statistics of the evening EMAs, 21.5% of participants reported that they competed with Fitbit friends via the Fitbit app (see Table 4.8). Within the Fitbit app, not that many people used the competition function, but the few participants who used this function stated that competing motivated them a lot. Statistically, when a participant competed via Fitbit app, that correlated positively with evening step counts (he or she would walk more by 2292.82 number of steps ($p<0.01$) (see Table 4.10)). During an interview, participant 12, who competed with her husband, stated that she checked his steps taken during the day. If she realized that she had fewer steps than she wanted for competition (she was behind her husband), she would try to take more steps during and after work.

Interviewer (Me): *Do you have a Fitbit friend who can compete with you?*

Participant 12: *Yes, I'm competing with my husband via Fitbit app almost every day.*

Interviewer (Me): *Do you think it is motivating you to do more steps?*

Participant 12: *Absolutely, yes. If my husband's steps go up and I'm behind him, I also try to take more steps during lunchtime or after work to beat him.*

**Table 5.2 Summary of relation between EMA Morning and Evening Independent Variables and Morning and Evening Self-report Steps Counts**

| Dependent Variables | Independent Variables |
|---|---|
| ***1. Morning Steps Data***<br>*:Reported by the user after checking the step data on the Fitbit device during the morning EMA survey* | **From Morning EMA**<br>[**Morning** Mood state: Good] **Negative**<br>[**Morning** Mood state: Tired] **Negative**<br>[**Morning** Physical activity level: Very Light] **Negative**<br>[**Morning** Physical activity level: Moderately Vigorous Plus] **Positive**<br>[**Morning** Physical activity level: Vigorous] **Positive** |
| ***2. Evening Steps Data***<br>***:*** *Reported by the user after checking the step data on the Fitbit device during the evening EMA survey* | **From Evening EMA**<br>[Left the office = Yes] **Positive**<br>[**Evening** Mood state: Joyful] **Negative**<br>[**Evening** Physical activity level: Moderately Vigorous Plus] **Positive**<br>[**Today's** physical Activity: Use stairs instead of elevators] **Positive**<br>[**Today's** Physical Activity: Other (e.g., riding bicycle)] **Positive**<br>[**Today**: Competed using Fitbit app] **Positive** |

### 5.1.2 Relationship between EMA Morning and Evening Independent Variables and Steps Taken and Active Minutes from Fitbit Log

In this section, I will describe the relationships between morning and evening EMA correlations with total steps taken and active minutes of the day from participants' Fitbit log data. The total steps taken and total activity minutes were calculated by end of the day and time-stamped in order to be aligned with EMA surveys. Through this method, I could see what contextual factors (for morning and evening EMAs) correlated with total steps taken and active minutes of the day.

#### 5.1.2.1 Relationship between EMA Morning and Evening Independent Variables and Step Count for the Day from Fitbit Log

1) **Morning EMA** [Feelings checked data: Motivated] **Positive**

The answers to the question of "How did you feel when you checked the data provided by Fitbit?" (answer choices: 1) It motivates me a lot (60%), 2) It motivates me a little (31.85%), 3) It does not motivate me at all (0.74%), 4) I have no idea (4.44%) (see Table 4.7)) had correlations with the number of steps for each daytime period (not morning step count data). This question was asked only during morning EMA. As we can see in section 5.1.1.1, feelings checked data: Motivated does not have a significant correlation with the morning step count dependent variable. This factor correlates with the total steps for the day. This means that when participants reported that checking data was motivating them in the morning, that lead to the participants walking more by 2771.41 ($p<0.01$) number of steps per day after morning EMAs were submitted (after 9:00 to 11:00 a.m.). I asked similar questions during interviews about how participants felt when they checked their data in the morning and how this affected their movement during the day. Participant 6 stated that the most motivation to move more and take more steps came from checking his data.

Interviewer (Me): *Which of the features have had a major impact on your activity and motivate you to move more, such as goal setting or competing with your Fitbit friends?*

Participant (P6): *Monitoring and recording my activity motivates me a lot. Seeing that record and data seems to be motivating me a lot.*

Furthermore, participant 8 stated that not only checking their current step count data in the morning, but also the data from the previous day motivated them a lot to move more during a given day.

Participant (P8): *On my way to work in the morning, I checked the data to see how far I'd walked today and also how much I had walked yesterday.*

Interviewer (Me): *So, when you see that data, are you motivated?*

Participant (P8): *Yes, that's right. I think I feel motivated by seeing the data. If I had a lower number of steps yesterday, I try to walk a little more today.*

Participants may check their data multiple times during a day, but my data analysis suggests that after checking Fitbit data in the morning, they at least exercised more in the afternoon, leading to increased total steps for the day.

2) **Evening EMA [Today (Daytime)**: Competed Using Fitbit App] **Positive**

Similar to section 5.1.1.2 (Relationship between evening step count and evening EMA), when participants had competed using the Fitbit app, this also had a statistically significant correlation with the number of *total steps taken* for the day. When participants competed using the Fitbit app, walked more by 6407.43 number of steps ($p<0.01$) per day. As mentioned above, one of the participants (P12) tried to take more steps during work and also after work. As this information overlaps with the above section (5.1.1.2, #5), I will not explain it in further detail.

3) **Evening EMA [Evening** activity level: Moderately Vigorous] Positive

Similar to section 5.1.1.2 (Relationship Between Evening Step Count and Evening EMA), a Moderately Vigorous activity level (e.g., walking at a brisk pace, weight lifting, aerobics) has a statistically significant correlation with the total number of steps for the day. Participants reported that if they did Moderately Vigorous activities, they may walk more by 65523.87($p < 0.05$). It overlaps with above section (5.1.1.2, #5), I will not explain in more detail.

#### 5.1.2.2 Relationship between EMA Morning and Evening Independent Variables and Activity Minutes from Fitbit Log

Before discussing the relationship between the morning and evening independent variables and the physical activity intensity levels, I explain Fitbit's "active minutes" measure and how it is calculated.

The Fitbit device provides several physical activity levels: light (lightly) active, moderately (fairly) active, and vigorous (very) active (all measured in minutes; see Table 5.4). Fitbit calculates active minutes as shown in Figure 5.1 (a screenshot of the user dashboard). This measure is calculated based on metabolic equivalent (MET), a widely used indicator of physical activity intensity. The MET table is divided into 6 stages: 1) very light (1 – 1.5 MET), which includes sedentary activities such as watching TV or riding in a car (1.0 MET), or reading while sitting (1.3 MET); 2) light and 3) light-plus (1.6 – 3.0 MET), such as cooking, light office work, working at a computer or desk, and eating; 4) moderately vigorous and 5) moderately vigorous-plus (3 – 6 MET), such as walking at a brisk pace or weightlifting; and 6) vigorous (more than 6 MET), such as bicycling, jogging, and hiking (Norton & Sadgrove 2010; Ainsworth et al. 2000).

I also mentioned the MET table (Table 5.3) in Chapter 3 (Methods) because I also used the physical activity level indicator to determine the participants' level of physical activity during the pre-questionnaire period and the EMA survey period.

**Table 5.3 Metabolic Equivalents Table (Ainsworth et al. 1993)**

| Activity Level | MET | Examples of Activity |
|---|---|---|
| Very Light | 1 - 1.5 METs | Standing, Reading, talking on telephone, Sitting in class, studying, note taking |
| Light | 2 METs | Walking at a slow pace (1-2 mi/hr), playing musical instrument, Light gardening, Light office work, light use of hand tools |
| Light Plus | 2.5 - < 3 METs | Walking downstairs, Cooking, light housekeeping, shopping, Pushing stroller with child, walking dog, Walking at an average pace (2-2.5 mi/hr), slow dancing, Golf bowling, fishing |
| Moderately Vigorous | 3 - 4 METs | Walking at a brisk pace (1 mi every 20 min), Weight lifting, water aerobics, Walking on job, 3 mph (one mile every twenty minutes), in office |
| Moderately Vigorous Plus | 4.5 - 6 METs | Slow swimming, Most doubles tennis, Dancing (more rapid), Golf |
| Vigorous | > 6 - 10 METs | Hiking, Jogging (1 mile every 12 min), Skiing, Tennis, Bicycling |

Fitbit company describes their measured activities levels at three levels (Lightly Active/Fairly Active/Very Active) of granularity. Their definitions are below:

[Fitbit Term] **Lightly Active** (light-intensity physical activity) [< 3 MET]

**Fairly Active** (moderate-intensity physical activity) [3–6 MET]

**Very Active** (vigorous-intensity physical activity) [6+ MET]

As Fitbit corporation recommended, Fitbit calculates users' MET values based on the intensity of their physical activity (Fitbit, 2017). For example, 1 MET is the energy used while seated or sitting quietly, with the body at rest. From 1 to 3 MET is regarded as light-intensity physical activity (corresponding to *Lightly Active* in Table 5.4). From 3 to 6 MET is regarded as moderate-intensity physical activity (corresponding to *Fairly Activ*e in Table 5.4). Greater than 6 MET is regarded as vigorous-intensity physical activity (corresponding to *Very Active* in Table 5.4). Fitbit users earn active minutes for activities of at least 3 MET; these minutes are only earned after "10 minutes of continuous moderate-to vigorous-intensity exercise" (Fitbit, 2017). The WHO (World Health Organization)'s recommendation is to engage in 150 minutes of moderate-intensity of physical activity and 75 minutes of vigorous-intensity exercise per week (WHO, 2015). Therefore, it is important to know and understand the intensity of people's physical activity.

**Figure 5.1 Screenshot of the Fitbit Dashboard (Resources from Google Image)**

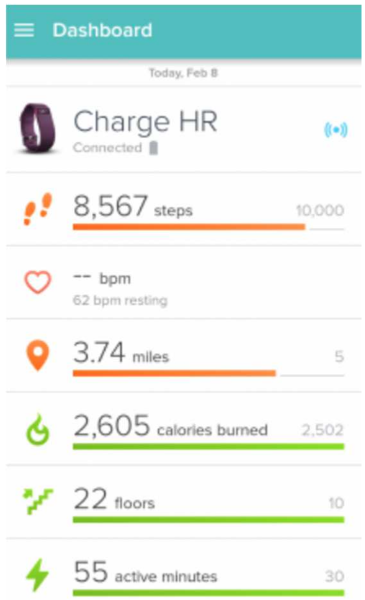



Table 5.4 shows the 27 participants' mean values for steps, total active, *lightly active*, f*airly active*, and *very active* for the 5 days of the EMA survey period. According to the universal 10,000-steps-per-day goal(Tudor-Locke and Bassett 2004), the participants' mean number of steps for the 5 days of the EMA survey was relatively high.

The amount of lightly active (in minutes per day) was calculated from Fitbit data (Table 5.4); this corresponded with the sum of the light and light-plus activity measures in the MET table, with a metabolic equivalent of between 1.6 and 3.0 MET. During the 5 days of the EMA survey period, the participants mostly engaged in lightly-intensity activities (averaging 199.53 minutes per day); this result was in line with the answers to two of the EMA's survey questions: "What level of physical activity did you engage in this morning?" and "What level of physical activity did you engage in this evening?" The participants reported that they mainly performed light (morning: 40.8%; evening: 37.7%) and light-plus (morning: 10.6%; evening: 14%) levels of physical activity (see Table 4.8). Only a few participants reported that they engaged in moderately vigorous (morning: 2.8%; evening: 2.6%), moderately vigorous-plus (morning: 3.7%; evening: 1.5%), or vigorous (morning: 1.4%; evening: 3%) activity.

**Table 5.4 Summary of Participants' Mean of Steps, Activite Minutes of Intensity Level of Activity during EMA Survey Period**

| Mean of Number of Steps | Mean Total Active **(minutes)** | Mean Lightly Active **(minutes)** | Mean Fairly Active **(minutes)** | Mean Very Active **(minutes)** |
|---|---|---|---|---|
| 10988.16 | 257.16 | 199.53 | 24.30 | 33.33 |

In this part, I describe the significant factors that correlate with total activity and each of the three activity levels. Of these factors, I do not explain those that I already described in the previous section, such as the positive correlations with competing using the Fitbit app [Today: Competed using Fitbit app: **Positive**] and with users feeling "motivated" [Feelings checked data: Motivated: **Positive**].

In particular, I describe which contextual factors actually affect (or interact with) the amount of moderate- to vigorous-intensity physical activity.

1) Minutes of Total Activity Levels (Lightly, Fairly, Very) of the **Day:** [Number of checked Fitbit data via Device] **Positive**

During the evening EMA survey, I asked "How many times have you checked your data via the Fitbit device today?" This response showed an interaction with that day's total activity minutes. Statistical analysis showed that, when participants checked their data via the Fitbit more often, there was a positive interaction of 24.64 minutes ($p < .01$). However, this interaction could differ based on personal traits.

Someone who worries about reaching a step goal is more likely to check his or her data. The qualitative interviews support this hypothesis.

For instance, Participant 10 checked her data during the workday to help reach her daily preset step goal:

> Interviewer (Me): *What do you think is the best thing about this device?*
>
> Participant 10: *The best thing? It was just... numerical things. ... It was nice to be able to visualize how much I ate and how much I walked. This provides a goal, so I could see a number to reach that target goal. It is important that I achieve my goal each day, so I had to check the data frequently during work to reach the goal.*

On the other hand, Participant 9 exercised regularly, knew his exercise patterns, and could tell when he met his goal; however, he really didn't care much about the goal, so he didn't check his data frequently.

> Interviewer (Me): *Then, of the device, mobile app, and website, which one do you use the most to check your data?*
>
> Participant 9: *I check the app once a day. I check the web once a week. I do not check the device often.*
>
> Interviewer: *You didn't check the data often using your Fitbit device?*
>
> Participant 9: *Right. I exercise regularly now, and I know my pattern. I just think that I usually meet the goal, so I do not check it separately. Actually, I don't care that much about the step goal.*

2) Activities-Minutes **Fairly** Active of the **Day**

Fairly active corresponds to 3 – 6 MET (Table 5.3). Participants earn fairly active minutes when they engage in moderate-intensity physical activity, which includes walking at a brisk pace (20 min/mile; 3.5 MET), weightlifting (3.5 MET), swimming slowly (4.5 MET), and golfing (5 MET)(Norton, & Sadgrove, 2010).

2-1) **Morning EMA**: [**Morning** Level of Stress] **Negative**

During the morning EMA survey, the participants were asked to provide their current level of stress on a Likert scale from 1 (*not at all*) to 5 (*very stressed*). Interestingly, stress level only interacted with the moderate-intensity level of activity (fairly active). As stress levels increased, a negative interaction with moderate-intensity activity (fairly active) (-11.28 minutes) was observed. The participants usually relieved their stress by doing physical activities; however, my analysis suggests that stress could influence indicators of physical activity and exercise. This in line with existing studies, which showed that stress can be an important barrier to achieving a healthy level of  physical activity (Lutz, Stults-Kolehmainen, & Bartholomew 2010; Stults-Kolehmainen & Sinha 2014). During an interview, Participant 3 stated that he doesn't like to engage in more physical activity when he is stressed:

Interviewer (Me): *Do you get a lot of stress at work?*

Participant 3: *Yes, I'm the kind of person who gets a stressed a lot.*

Interviewer: *When you have more stress, is there something that you do? Perhaps you walk more or exercise more? Or walk less?*

Participant 3: *Actually, if I get stressed, I do try to work out a little bit more, but when I get a lot of stress, I'm more likely to just go home and rest.*

This may suggest that people encounter low to moderate levels of stress at work, they will tend to do more exercise because it helps relieve stress, but when they are very stressed they may instead retreat to a safe space (home) and not engage in exercise. Aldana et al. (1996) study supports the result that the group with high perceived stress was less likely to perform physical activity than the group with moderate perceived stress. Therefore, having a lot of stress negatively affects physical activity.

2-2) **Evening EMA**: [**Evening** Mood state: Depression] **Negative**

During the evening EMA, I asked the participants about their moods. The results show that evening depression has a negative interaction (correlation) with moderate-intensity activity (fairly active) (-73.18 minutes). This means that participants who reported a depressed mood when they submitted their evening EMA also engaged in less moderate-intensity physical activity after work, relative to other participants. My study results indicated depression could interaction negatively, reduction of the level of physical activity, especially moderate intensity of physical activity. This is in line with the previous study, which showed that depression can negatively affect physical activity (Roshanaei-Moghaddam, Katon, & Russo, 2009). Especially, Silva et al. (2012) study discovered that people with depression were more likely not to engage in physical activity at the recommended levels which described as "at least 30 min a day of at least moderate intensity on at least 5 days of the week".

A previous study pointed out that the firmly established link between depression and pysical activity—that is, depression reduces physical activity—suggests that a similar trend may exist for stress and physical activity (Stults-Kolehmainen & Sinha, 2014). This means that both depression and stress affect physical activity.

2-3) **Evening EMA**: [**Today** Total Working Hours of the Day] **Negative**

I asked participants about the total hours they worked in the day, and the results show that, total work hours had a negative interaction with moderate-intensity physical activity (-12.457 minutes). This result matches with leaving work earlier (left the office = "yes") and thus with having fewer hours in the work day, which allows more time for other activities, including exercise (5.1.1.2, section #1). Those who work until late at night have fewer opportunities to engage in moderate-intensity exercise than do those who go home earlier.

2-4) **Evening EMA: [Evening:** Activity Level: Moderately Vigorous] **Positive**

Interestingly, when I asked participants about their levels of physical activity during the afternoon, their reports of engaging in moderately vigorous activity (e.g., weight lifting or aerobics), strongly corresponded to fairly active minutes. This means that what the participants reported they were doing matched well with the Fitbit reports, so the reliability of using the EMA method in place of Fitbit data was high when considering the users' contextual factors.

3) Activities-Minutes **Very** Active of the **Day**

3-1) **Evening EMA** [**Evening** Activity Level: Vigorous] **Positive**

These results are similar to the above results. When participants reported that they engaged in vigorous activity in the afternoon (e.g., jogging or cycling), there was a strong positive relationship with the amount of very active minutes, which corresponds with a vigorous level of activity. This means participants reported what they were doing exactly and that the reliability of using the EMA method in place of the Fitbit data was high when considering the users' contextual factors.

**Table 5.5 Summary of the Relationship between EMA Morning and Evening Responses as Independent Variables and the Daily Fitbit Data as a Dependent Variables: Analysis of Daily Fitbit Data and EMA Data**

| Dependent Variables | Independent Variables |
|---|---|
| ***1.** Steps of the **Day** provided by Fitbit* | **Morning EMA**<br>[**Morning:** Feelings checked data: Motivated] **Positive**<br><br>**Evening EMA**<br>[**Today:** Competed using Fitbit app] **Positive**<br>[**Evening's** activity level: Moderately Vigorous] **Positive** |
| ***2.** Minutes of Total activity levels (Lightly, Fairly, Very) of the **Day** provided by Fitbit* | **Morning EMA**<br>[Feelings checked data: Motivated] **Positive**<br><br>**Evening EMA**<br>[**Today:** Competed using Fitbit app] **Positive**<br>[**Today's** Number of checked Fitbit data via Device] **Positive** |
| ***2.1** Activities-Minutes Lightly Active of the **Day** provided by Fitbit* | **Morning EMA**<br>[Feelings checked data: Motivated] **Positive**<br><br>**Evening EMA**<br>[**Today:** Competed using Fitbit app] **Positive**<br>[**Today's** Number of checked Fitbit data via Device] **Positive** |
| ***2.2** Activities-Minutes Fairly Active of the **Day** provided by Fitbit* | **Morning EMA**<br>[**Morning** Level of Stress] **Negative**<br>[Feelings checked data: Motivated] **Positive**<br><br>**Evening EMA**<br>[**Evening** Mood state: Depression] **Negative**<br>[**Today:** Competed using Fitbit app] **Positive**<br>[**Today's** Total Working Hours of the day] **Negative**<br>[**Evening's** activity Level: Moderately Vigorous] **Positive** |
| ***2.3** Activities-Minutes Very Active of the **Day** provided by Fitbit* | **Morning EMA**<br>[**Morning's** number of checked Fitbit data] **Positive**<br><br>**Evening EMA**<br>[**Evening's** Activity Level: Vigorous] **Positive** |

## 5.2 Five Elements for Model Proposal

By using both inductive and deductive analysis methods, I provided findings that demonstrate how the context of everyday life affects physical activity steps through the use of wearable devices. For deductive analysis, I derived important concepts and elements from information behavior theory based upon Wilson's models of information behavior(Wilson, 1981b, 1997) and information practices (everyday information practices) theory based upon McKenzie's (2013) and Hektor's (2001) models of information behavior in everyday life. Mainly, my analysis derived concepts and elements from Hektor's model of everyday life. For inductive analysis, 27 interviews' transcriptions were used to define patterns and themes from office workers' wearable activity tracker use in everyday life.

Based on these deductive and inductive processes, I defined five elements: environment, information and communications technology (ICT), contextual factors, information activities, and life activities. In my study, information activities (information behaviors) were classified differently from life activities (everyday behaviors). Instead of focusing on information behavior (information activities) as a starting point, my research focused on identifying a few everyday activities and individual environmental factors, then tracking and analyzing those behaviors. The use of information systems in everyday life constitutes the context of the situation. Perhaps it may not be possible to comprehensively study the significance of the overall situation, but researchers can choose a few situations that are key to building a complex whole (Hektor, 2001). Therefore, my study concentrated on how the context of office workers' everyday life relates to the physical activity of steps taken during the day through the use of wearable activity trackers.

**Five elements: Environment, Information and Communication Technology, Individual Contextual Factors, Information Activities, and Life Activities**

In this section, each element is described from previous literature. Hektor (2001) described the contextual elements of an 'environment' as including the social and physical location of people and their activities (Hektor, 2001). He also stated that it is important to understand situations and contexts to make sense of information behavior in an environment (Hektor, 2001). In my study, the environment was comprised of an office work environment, which could impact participants' daily lives and even moods.

To understand everyday activities (life activities), I've researched literature in the domain of everyday life. My study distinguished information activities (information behaviors) from life activities (everyday behaviors). Hektor (2001) mentioned that distinguishing information behavior from everyday activities as two groupings of activities that make up everyday life may benefit any research in the everyday life domain. To understand what situations can be expected in everyday life, Ellegard (1999) established categories of everyday activities. Figure 5.2 describes the top two categories of activities in everyday life. Hektor defined life activities as 'corporeal movements in space and time that imply the manipulation of physical reality' (2001, p.68). Every physical activity performed in our daily lives falls into one of the categories in Figure 5.2. This approach does not consider information activity. Information activities are defined as 'any activities that involve mediated or unmediated communication of information' (Hektor, 2001, p.69). Information activities differ from life activities by emphasizing and orienting information rather than physical tasks (Hektor, 2001). Based on these concepts, I defined a few everyday life activities *a priori*, then tracked and analyzed them.

Hektor defined information behavior as the problem of seeking, gathering, communicating, and giving information (2001). Mackenzie identified seven modes in information practices: (a) Information Needs, then the informational practices of (b) Active Seeking, (c) Active Scanning, (d) Non-directed Monitoring, (e) Receiving Information by Proxy, (f) Sharing Information, and (g) Participating. I used both Hektor's (2001) and Mackenzie's (2003) information practices to justify my research participant information behavior in the use of wearable trackers in everyday life.

Individual contextual factors are composed of social and physical context, and also include personal characteristics. Previous evidence already emphasizes the roles of social and physical context in influencing health behaviors (Ullmann, Goldman, & Pebley 2013; McNeill et al., 2012). Furthermore, many researchers in the field of information behavior emphasized the importance of certain contextual factors that influence information behavior (Al-Suqri, 2014). Wilson's revised second-model approach also stressed contextual factors in information behavior (Twilson, 1997). In my dissertation, by using the novel data collection method of EMA, I discovered integral contextual factors that could influence physical activity changes in the use of wearable devices in everyday life.

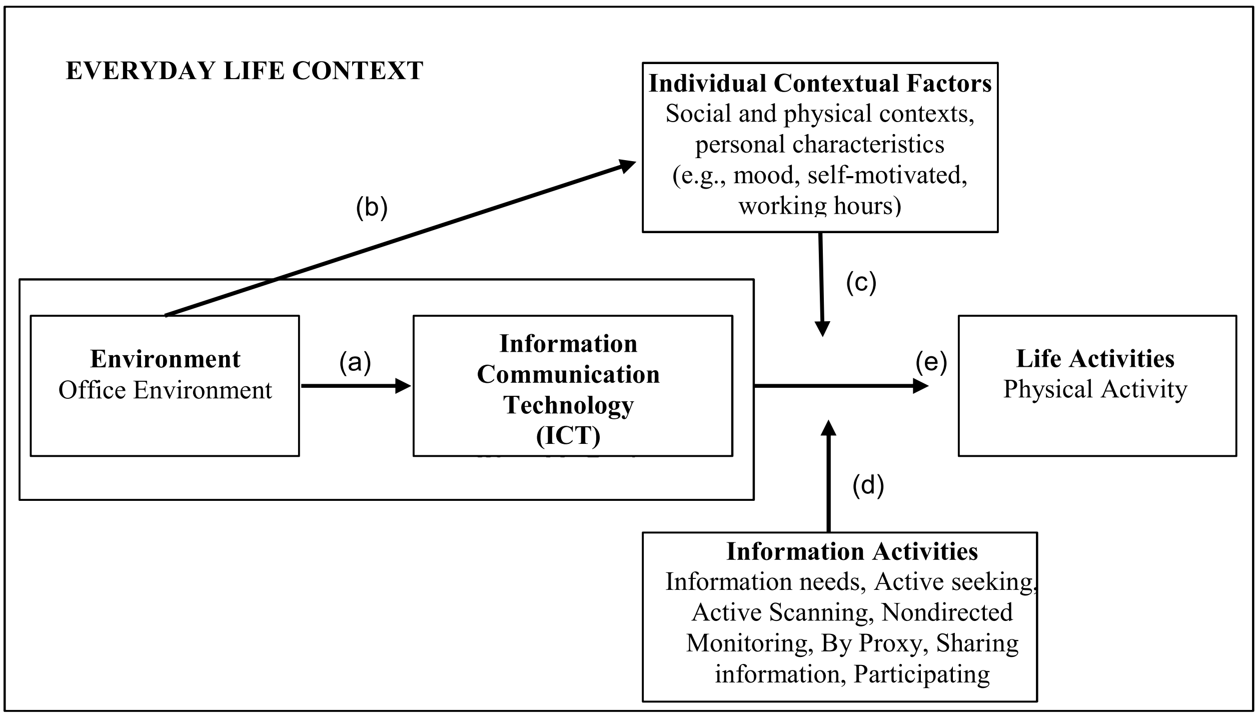
**Figure 5.2 Top Two Categories of Activities in Everyday Life (Ellegar, 1999)**

| Level 1-categories | Level 2-categories |
|---|---|
| Caring for oneself | Eating / Sleeping / Personal hygiene / Going out-coming home |
| Caring for others | Feeding / Clothing / Hygienic care / Playing / Bring together with others / Put to bed / Aiding & Rising |
| Household care | Cleaning / Mending clothes / Mending things / Household administration / Purchases / Gardening / Construction work |
| Reflection and recreation | Social relaxation (e.g. entertaining guests, speaking on the phone) / Personal relaxation (e.g. reading, watching TV, listening to music, pursuing hobby) |
| Transportation | Transportation of oneself |
| Procure and prepare food | Acquiring / Preparing / After-work |
| Gainful employment | Working |

### 5.3 Proposing a Model Based on Analysis and Findings

The following figure is a diagrammatic model proposed based on my findings to further elaborate my discussion. In this section, the critical themes are described which support the diagram (Figure 5.3).

**Figure 5.3 Proposed Model: Relation between Environment, Technology, Individual Contextual Factors, Information Activities, and Life Activities** ((a), (b), (c), (d), and (e) explain the interaction between the elements, and the arrow does not imply the sequence)




### 5.3.1 Theme 1: The Environment Makes People Use ICT (Figure 5.4 (a))

Figure 5.4 (a) shows the process by which the environment itself makes people use information technology. Hektor defined an environment as a "starting point for action" and a place "where the people meet with the technologies that mediate information" (2001, p.61). In my study, the environment is a work environment where office workers work in an everyday context. My qualitative data findings show how the environment itself makes my participants (office workers) use their technology (Fitbit devices).

Based on interview data, office workers reported that they did not have time to work out in a weekday. The majority of people in the study worked for a long time until late at night, stating that they did not have time to exercise separately. Office workers tried to find ways to move a little more in their workplace in daily life. Because it was difficult to find some time to do proper exercises (because they could not spare too much time to exercise), participants would try to find ways to work in short bits of exercise during the everyday life, like walking up stairs instead of taking the elevator. In order to know if they were getting enough, or at least more exercise, the participants adopted this device and used to monitor their physical activity patterns in daily life and to improve them. Interestingly, most participants stated that they were willing to try to find ways to exercise by walking more in everyday life, and that's why they wanted to use the devices. P19 stated that he may not need a Fitbit device if he/she could spare some time to go to the gym. Since P19 cannot do that in daily life, he/she tried to find a way to do more physical activity in daily life by using the device. Thus, for people already finding time to do plenty of exercise there may not be as much motivation, but for those having difficulty finding the time in their day to get sufficient exercise it can be helpful.

> *Participant (P19): If I can spare some time go to the gym or go to exercise in earnest,* ***I think I may not need this [Fitbit] device.*** *But I cannot do that, and instead, I tend to work out in everyday life and motivate myself,* ***so I try to make up for that by walking in commute time.*** *As I said, if I was willing to spend some time running and doing other exercises, I would not have needed this [Fitbit] device.*
>
> *Interviewer (Me): Indeed. Could it be the case that you use it [Fitbit] more to find out how you do in your daily life?*
>
> *Participant (P19): What I most often do is, when commuting to work, I walk about 3km on my way to work instead of riding a bus and coming back home walking as well. I set my goal to reach 10,000 steps a day, so I try to walk and achieve it when commuting. When I drive to work, I go out and walk during the lunchtime. And by doing so I have been trying to achieve my goal.*

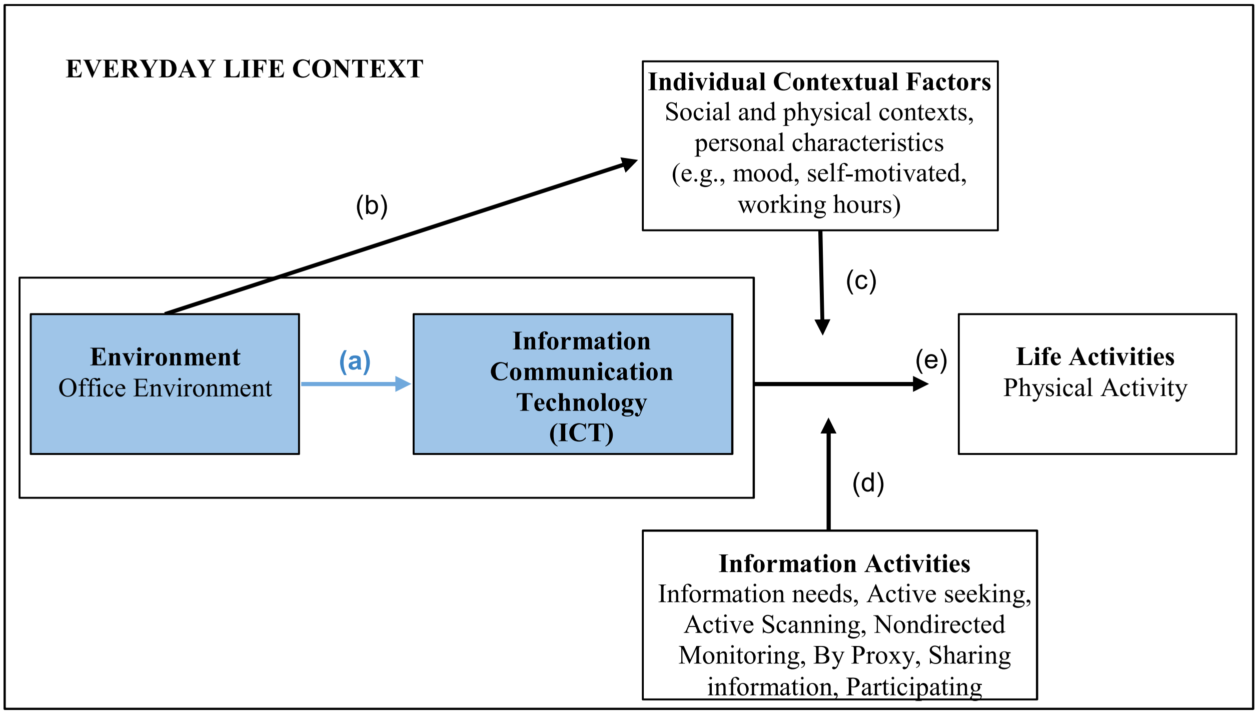
In a similar fashion, during an interview, I asked a participant's motivation to start using the device. The participant reported that they wanted to start using the device to find a physical activity pattern in everyday life. P26 stated that she wanted to check her usual life pattern (to see how much she/he walked in daily life) by using the Fitbit:

*Participant (P26): First of all, I wanted to figure out something like life pattern. Sleeping time or how much I walk in a day..something like that. Before I used this Fitbit, I wore a pedometer and checked how much I walked a day. It was just that level, but with that I could not have previous records unless I recorded it manually. However, with this Fitbit I can check [my previous steps information] in the app and the record is accumulated. I want to see something statistically like this, therefore I chose to use this device. I wanted to check my usual life pattern.*

*Interviewer (Me): So, that means you wanted to find a pattern while living an ordinary life such as going to work, right?*
*Participant (P26): Yes, what I wanted to know was something like how much I walk and how long I sleep and heart beats. Those are the three main things that I wanted to know.*

My findings show how the environment affects technology use, and how the use of a device begins depending on the environment. Understanding the environment is key to designing better information technology that leads to meaningful behavior changes.

**Figure 5.4 Highlited "The Environment Makes People Use ICT"** ((a), (b), (c), (d), and (e) explain the interaction between the elements, and the arrow does not imply the sequence)




### 5.3.2 Theme 2: Individual Contextual Factors Affected by Environment (Figure 5.5 (b))

To understand individual contextual factors, we need to understand that individual contextual factors are affected by their environment (Figure 5.5 (b)). For example, my participants were office workers who worked in an office setting (environment) in which they sat all day with a computer at a desk. These factors affect participants' physical activity levels in daily life. They mostly spent sedentary time during work hours. EMA descriptive results from 27 adopters supported this assertion (or situation).

During the EMA period, the response of their sedentary time during their shifts on that day was 7 hours (37.85%), which was the most common answer. Furthermore, despite participants considerably reporting that their favorite types of PA levels were moderately vigorous, moderately vigorous plus, and vigorous (51.8% combined), the participants usually performed at a very light (41.1%) (e.g., reading, standing, talking, sitting in office, studying) or light (37.7%) (e.g., walking at a slow pace, light office work) level of physical activity during a working day (See Table 4.3). Interview transcripts also supported that participants were usually sedentary during working hours:

1. *Participant (P4): I usually work from 8am to 5pm. That is my regular shift.*

   *Interviewer (Me): But it seems you work for quite a long time. You checked [in the survey] that you work more than 8 hours a day.*

   *Participant (P4): Yes. I cannot leave work for home on time… As a matter of fact, I do not walk till lunchtime once I sit down at my desk in the morning.… So, there is no time to walk… In our company we have a Happy Road for walking... But after lunch time, I usually come back to my seat and spend time with my smartphone or computer while sitting at my desk.*

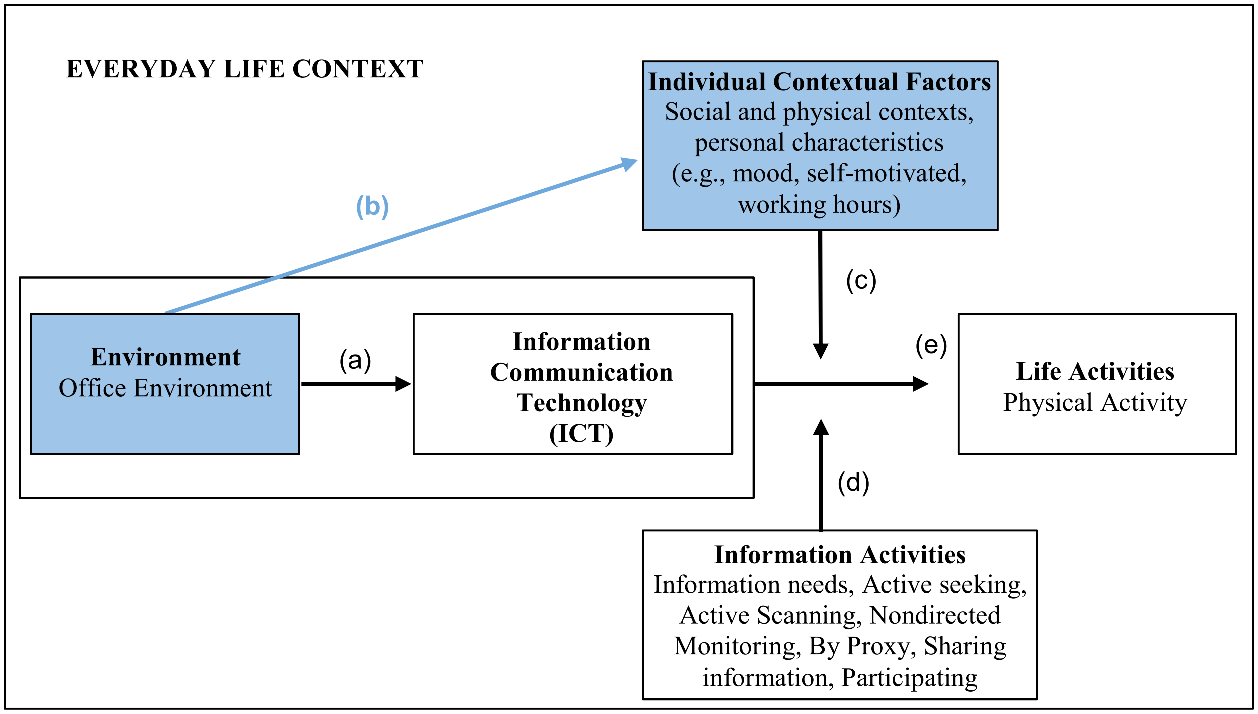
2. *Interviewer (Me): Do you have some time to walk or take any other exercise in your office?*

   *Participant (P6): No... Seldom. I usually work in a sedentary position, and my workstation does not have a big radius of movement.*

3. *Interviewer (Me): Do you have time to stand up and have some break time during work?*

   *Participant (P9): Typically, I usually spend my time in a sitting position. I stand up only when I go to the toilet or want to drink water.*

**Figure 5.5 Highlighted "Individual Contextual Factors Affected by Environment** ((a), (b), (c), (d), and (e) explain the interaction between the elements, and the arrow does not imply the sequence)




### 5.3.3 Theme 3: Individual Contextual Factors Affect Life Activities in the Use of Wearable Activity Tracking Device (Figure 5.6 (c))

Individual contextual factors are composed of social and physical contexts and also include personal characteristics, from motivation, mood, and stress to level of daily physical activity (McNeill et al. 2012). There are limited studies that stress the role of contextual factors and how these affect physical activity in the use of activity tracking devices in daily life. By using the EMA data method, I found integral contextual factors that could influence changes in the use of wearable devices in everyday life.

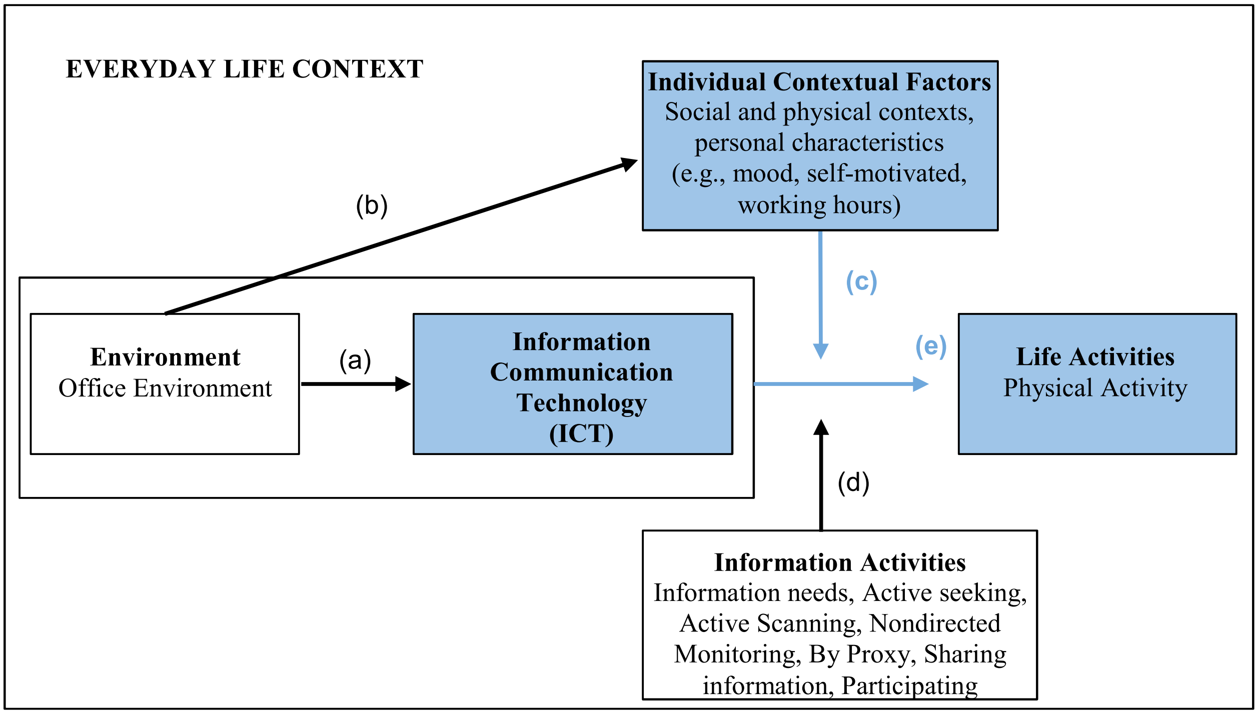
As shown in summary Table 5.2 and 5.5 in the Section 5.1 (EMA Analysis and Qualitative Interview Data), contextual factors that affected physical activity in daily life, as well as the use of an activity tracking device, were described. For example, a person's stress level reported through morning EMA has a statistically significant interaction with the moderate-intensity level of physical activity of the day. As stress increased, a negative interaction with activity minutes of moderate-intensity level (fairly active) (-11.38 minutes) was observed.

During a session in the EMA data collection period, I asked participants to provide their current level of stress in morning EMA. Most participants got stressed, registering least stressed (40%), somewhat stressed (23.7%), and extremely stressed (18.5%) (see Table 4.7). These results indicated that my participants suffered from stress when they worked. The stress level, which we regarded as a contextual factor, is affected by the environment. As mentioned in chapter 3, Korean office workers work among the highest average annual work hours in OECD countries. According to a report provided by the Samsung Economic Research Institute, Korea has the highest level of stress and lowest job satisfaction among OECD countries (Jung, 2010).

Other than the contextual factors, chapter 5.1 describes all the contextual factors that I discovered through my research that have significant effects on physical activity.

In order to study the usage patterns of information technology and to see what factors affect increased physical activity in the use of devices, it is necessary to investigate and understand users' environments and the contextual factors that come from them (Scherer, Craddock, & Mackeogh, 2011).

**Figure 5.6 Highlited "Individual Contextual Factors Affect Life Activities in the Use of Wearable Activity Tracking Device"** ((a), (b), (c), (d), and (e) explain the interaction between the elements, and the arrow does not imply the sequence)




### 5.3.4 Theme 4: Information Activities (Practices) that Affect Life Activities in the Use of the Wearable Activity Tracking Device (Figure 5.7, (d))

Hektor defined information activities as "the sets of behavior that people display in their interaction with information" (Hektor, 2001, p. 62). He described information behavior as seeking, gathering, communicating, and giving information. Similarly, Hektor's information behavior was described in line with McKenzie's everyday life-information practices (McKenzie, 2003) in information-seeking behavior. McKenzie identified 7 modes: (1) information needs, (2) active seeking, (3) active scanning, (4) nondirected monitoring, (5) by proxy, (6) sharing information, and (7) participating. Detailed descriptions of the McKenzie modes are described in the literature section of chapter 2. Information needs and active-seeking modes correspond to Hektor's information seeking and gathering.

Sharing information and participating modes correspond to Hektor's information communicating and giving information.

In a pre-interview questionnaire, the respondents selected the alternative that best described them on a Likert scale of 1(*never*) to 5 (*regularly*) for a revised questionnaire relating to McKenzie's information-practices model. This questionnaire results were described in chapter 4.1.5, in a section called "Information Behavior and Information Practices Descriptions".

In this following section, interview data was coded and focused on categories relating to McKenzie's model to provide a discussion of information activities that affect life activities (physical activity) in the use of the wearable activity tracker device. In addition, the results of information activities from EMA and McKenzie's pre-interview questions were incorporated.

#### 5.3.4.1 Information Needs

Wilson (1999a, p. 249) defined information behavior as "those activities a person may engage in when identifying his or her own needs for information, searching for such information in any way, and using or transferring that information." Based on Wilson's definition, people start to find some information for his or her own needs. Consistent with this definition, my research participants (wearable device adopters) started to use the device to obtain information on physical-activity patterns in everyday life based on their needs. Based on the McKenzie questionnaire, most participants (27 adopters) reported that they were *often* (n = 12, 44.4%) and *regularly* (n = 11, 40.7%) in need an information about physical activity and wearable activity trackers (Fitbit) or felt as if they should know more about them. The quotations below indicate that the participants' motivation for using the device was the need for life-pattern information.

Participant (P21): *When I work, I am sedentary so I just started to use the device to check how much exercise or walk I did or wanted to check the momentum I have. It is not easy to spare time for exercise anyway, so I would like to increase walking in everyday life.*

Wilson (2000) pointed out that the designers of information systems usually ask about how people are using the system rather than seek to determine what information people need and how information-seeking behavior relates to other behaviors which is more important to know (Wilson, 2000). Therefore, it is important to understand what the information needs are for information-system users to achieve better information flow and to design better systems that lead to meaningful behavior changes.

Surprisingly, in the use of the device, there were two interesting information needs that affected life activities. These life activities were changed based on user-information needs. The first information need was the desire by the participants to accumulate accurate Fitbit steps data. They did not want errors in their data, and they wanted Fitbit to calculate steps data that actually related to movements in everyday life. To make sure the data was accurate and reliable, participants took their wrist-worn Fitbit devices off when they used their wrists and hands for housework such as washing dishes:

*1.* Interviewer (Me): *Were there any restrictions on your activities when using the device?*
Participant (P3)*: Yes. [Fitbit] counts when I move my wrist. So [it counts] when I just move things—when I brush my hair, [apply] make-up, or [do] things like that, **I was afraid it would count**, so when I had to use my wrist a lot, I took it off. I wanted to make [sure] the **data was reliable**.*

*2.* Participant P(12): *When I did housework, I mostly put it [the Fitbit] in my pocket. When I had to use my hands a lot for washing, [even when I washed] my hands, I took it off. I was worried that the data would add more to what I [actually] did. **I wanted to make sure the data was accurate**.*

The above situations describe life activities that were changed in everyday life (taking off the device) based on information needs (making the data accurate). In exactly an opposite situation, life activities were changed based on information needs to create fake data to reach the steps goal in the use of the device. These participants tried to increase their numbers by shaking their arms because their information needs were to have steps numbers as high as possible.

1. Interviewer (Me)*: Were there any changes in your behavior after using this device*

   Participant (P5)*: No, I did not have much of that stuff, but [I did] move my arms to increase the number of steps at least once.*

   Interviewer (Me)*: Did you intentionally move your arm to increase the number to 10,000 steps?*

   Participant (P5)*: Yes. It could have just been my greed for the numbers. For example, if the number of steps was 9,000 or 9,500, then just [by] shaking [my] arm or something [like that, I could] reach 10,000.*

2. Participant (P17)*: What changed in my behavior was that I shook my arms intentionally when I walked because I had to increase the number of steps. I would say it [the Fitbit] correctly counted when I shook my arm enough. So, when I thought the data was falling short, I tended to shake my arm a lot.*

As seen above, information activities (information practices) were classified differently in my study from life activities (everyday behaviors) and described differently in terms of how they affected each other. Consequently, it is critical to understand information needs in everyday life when using an information system such as a wearable activity tracker to see how needs affect life activities.

#### 5.3.4.2 Monitoring (Information Gathering)

Hektor described a monitoring activity as an information-gathering behavior. The definition of monitoring in the Hektor model is appropriate to describe the monitoring of participants' physical activities (steps information) in the use of the device in the study. Hektor defined monitoring as " being directed to a familiar source that is regularly updated, where the monitoring, in part, reaffirms the agent by providing a stable and predictable form and, in part, supplies valued information" (Hektor, 2001, p. 83). Monitoring is not considered to be a searching activity because it does not imply a question or a lack of specific information (Hektor, 2002).

Interestingly, my research participants had a great deal of data accumulation as a result of monitoring their physical activities—step counts, sleep, and heart rates in everyday life. They also mentioned that collecting and accumulating data were the major reasons for continuing to use the device. All of the following quotations describe why they kept using the device:

1. Participant (P2): *I keep wearing the device for data management. I want to see the trend.*

2. Participant (P3): *If I do not wear it [Fitbit], I do not know how much I have moved... When I don't know, it makes me feel irritated (frustrated). That's why I keep using the device.*

3. Participant (P4): *If I don't wear it [Fitbit], the data can not be recorded.. As I cannot make data accumulation without it and I just want to collect data continuously so I keep using this device.*

4. Interviewer (Me): *Why do you keep using it when you use Fitbit?*
   Participant (P16): *I think I just want to have the data. I do not want to miss today's data. So,*

*I use this Fitbit continuously. (P16)*

5. Interviewer (Me): *I am curious that...do you walk more to do exercise? Or do you take exercise to fill the data to accomplish 10,000 steps goal?*

   Participant (P18)*: Honestly, I want to accomplish 10,000 steps first. I'm more interested in data and trying to reach the goal.*

6. *Participant (P6): Seeing that record seems to be motivating. If I wear it, it records all my movement. When I see the record, it gives me motivation. I am interested in data collection. That is why I am continuing using this device.*

Similarly, another reason participants continued to use the device was strongly attached to the data. Participant 4 stated there was concern about losing data because of the inability to use the device during a business trip.

1. *Participant (P4): Once I went to a business trip for three days and I forgot to bring a charger [for Fitbit] with me. I was very much worried if the battery would wear out so then I was afraid I would not be able to record the data. But luckily the battery lasted for 3 days. I was very nervous if I would lose data. Without battery, I could not record the data. It seems that I am somewhat obsessed by data collection. If data is deleted, I might feel very bad. The purpose of the use of this device is to record data.*

2. *Participant (P9): If I do not use it even for a while, the data will go away. So I think I'm trying not to take it off since I have used this device. I tend to be a bit obsessed to keep the data I've been*

*doing so far. Now I think I'm a little obsessed with the data. If I do not wear the device today, it will not be able to record. The meaning of the data is big to me.*

*3. Participant (P15): What is the reason that you have continuously used this device?*
*I think it is the obsession with data. So then I guess I can not change to another one [device or smartwatches]. Originally, I was going to change to Apple Watch, but I was reluctant to do this because I don't want to lose all the data that I recorded through Fitbit.*

*4. Participant (P18): I'm anxious when I do not take a device [Fitbit] with me. Therefore, I try to keep it with me all the time. Without it, I cannot collect data. I have anxiety about losing data.*

*5. Interviewer (Me): But if this data is gone (or you missed all the data) ... is that frustrating or so?*
*Participant (P5): Yes, I think so. I feel that it is a small asset. So if it goes away, I will be frustrated.*

Participants also used the data as a reflection of a moment in history. The data was used to check health conditions over time, and a previous week's data was used as a basic statistic for the next week.

*1. Interviewer (Me): You told me that you have worn it every day. What is the reason to wear it? Do you want to keep collecting data? Or do you feel emptiness when you do not wear it? Or some other reason..*

*Participant (P6) : For me data collection is the biggest reason. When I do not have a good condition, I check my sleeping time, calories and steps…If I do not have a good condition, I check the device more often as I can find the reason there.”*

*2. Participant (P9): On the weekends, I check the device for the week. I can see how much sleep I had, how many steps I walked, and what my weight was like. I think I'm using these as statistics. Then, I think next week I'll have to do something similar (overall, I have a concept of my life pattern). Or if I did not do much this week, I determine to walk more next week.*

As with the above, the majority of respondents of adopters were very interested in monitoring their data. Consistent with the qualitative findings, EMA analysis (Table 5.5) indicate that continuous monitoring ([Today's number of checked Fitbit data via Device]) of data through the device has a positive interaction with increasing activity minutes of physical activity. The EMA statistical analysis showed that, when participants checked their data via the Fitbit more often, there was a positive interaction of 24.64 minutes ($p < .01$).

**5.3.4.3 Active Seeking**

When they chose to buy a device, participants searched for people who had posted articles and reviews on wearable activity trackers. They often searched for information on mobile applications that work with Fitbit or for any firmware updates. They were also interested in information about what new devices had come out and how other users were using their wearable activity trackers. When they searched for information, the channels they used were Google, online discussion forum and even YouTube.

My participants—27 activity-tracker adopters—were pretty active in information seeking. The pre-questionnaire also indicated that the respondents reported that they *sometimes* (25.9%), *often* (33.3%), and *regularly* (14.8%) searched for people who had posted articles on wearable activity trackers and for information about whether there was a discussion forum page about the devices. The following are the participants' remarks about their practices of active seeking:

1. *Participant (P11): When I first bought [this device], I researched wearable-related things through Google, YouTube, and Cafes. I came to know Fitbit through an Internet search.*

2. *Interviewer (Me): Do you often (or sometimes) search for something like a Fitbit? What kind of information do you search?*

   *Participant (P18): Good reviews. I get information through reviews. I learn how I could use it. On the Fitbit Facebook page, there are a lot of [these kinds] of things. When I find one, I usually click on it. When I search, most of the searches fall under one of these two reasons: Either I want to know how others use it, or I want to buy something, especially when there is a new product. Yes, I want to see what the new product is like. I also want to read reviews by people who have already experienced it.*

3. *Interviewer (Me): So, did you go to the site in the beginning only. Are you still searching for information about Fitbit now? Or don't you do it anymore?*

   *Participant (P20): I usually use Google to check if there is a side app and if there are any firmware updates or other apps. I am interested in information on Fitbit, so I search for it often.*

#### 5.3.4.4 Active Scanning

Among 27 adopters, most participants reported they did not act on the information practice of active scanning, with 11 participants (40.7%) reporting never and 7 participants (25.9%) reporting that they rarely followed friends' Fitbit data to see their daily steps or to get information about their wearable activity trackers. This also corresponds with participant interviews, in which very few stated that they followed friends' Fitbit to see their daily steps. Participant 10, however, stated that she was following her husband's Fitbit to see his daily steps.

> *Participant (P10): My husband was added to my Fitbit friends list in my app. He is the only one I added to this list in my Fitbit app. I'm following my husband's data (number of steps). I'm looking at his data every day.*

#### 5.3.4.5 Nondirected Monitoring

A few participants reported they had received information about exercise and wearable activity trackers by chance when they were reading posts on social media. Of the participants, 40.7% *rarely* and 14.8% *never* received information about exercise and wearable activity trackers by chance through social media. Through the information practice of nondirected monitoring, the participants mainly used Facebook to receive information by chance. By adding a Fitbit user group as an interested group on Facebook, participants could receive information whenever new articles were posted.

> *Participant (P8)*: *I just visit Facebook to review articles whenever the management team posts articles on the Fitbit user-group page. I do not have to visit the group page; instead I can see any newly updated postings on my own Facebook page. I just see postings related to wearable activity trackers that I'm interested in. Like an online forum, I need to search some articles, but the Facebook page provides newly posted articles that have been uploaded through my interest-group page. I can see then on my timeline on Facebook.*

#### 5.3.4.6 By Proxy

A few participants (25.9%) *sometimes* asked other people to find information for them about wearable activity trackers and exercise. Interestingly, participants did not directly ask people offline; instead they asked other people online to find information for them. P19 stated that he wanted to figure out the brand of the wearable activity tracker that was worn by a celebrity on a TV show. So, he asked other people online to find the brand name for him:

> *Participant (P19): When I was watching TV, I saw the entertainer, Yoo Min-sang, wearing a device. For two weeks, he kept wearing the device on TV shows, and I thought it was pretty good looking. So I began looking the brand name. Then, I asked about it on an online forum. Other members of the forum found the brand name for me.*

#### 5.3.4.7 Sharing Information

Some participants used to share their tracking data with their friends and family using the Fitbit mobile app, text messages, or through their SNS (social network service). A few participants mentioned they shared their data at the beginning of their use of the device because of curiosity about sharing features, but after the curiosity wore off, they stopped using the device. Some participants hesitated to share their information with others.

> *Interviewer (Me*): Have you ever shared your tracking data through SNS?
>
> *Participant* (P5): Not at all. I don't like to add an online friend I really don't know. So, I also don't like to use SNS.
>
> *Interviewer:* Then, have you shared your data with your real friends or family?
>
> *Participant* (P5): No I haven't.

#### 5.3.4.8 Participating

The pre-interview questionnaire revealed that among 27 adopters, 7 respondents (25.9%) *often* participated in social networks or discussion groups related to Fitbit. With the same number of participants, 7 (25.9%) *never* participated in social networks or discussion groups related to Fitbit. Some participants took part in social networks or discussion groups, but others did not participate in discussion or social network groups related to Fitbit. Those who did participate often joined a group looking for an online friend to compete with through the Fitbit app, or to look for information on new products (devices).

> *Participant (P1): The reason I visited [the] Fitbit community and forum was that I was looking for a new product or a Fitbit friend in the neighborhood.*

**Figure 5.7 Highlited "Information Activities (Practices) that Affect Life Activities in the Use of the Wearable Activity Tracking Device"** ((a), (b), (c), (d), and (e) explain the interaction between the elements, and the arrow does not imply the sequence)

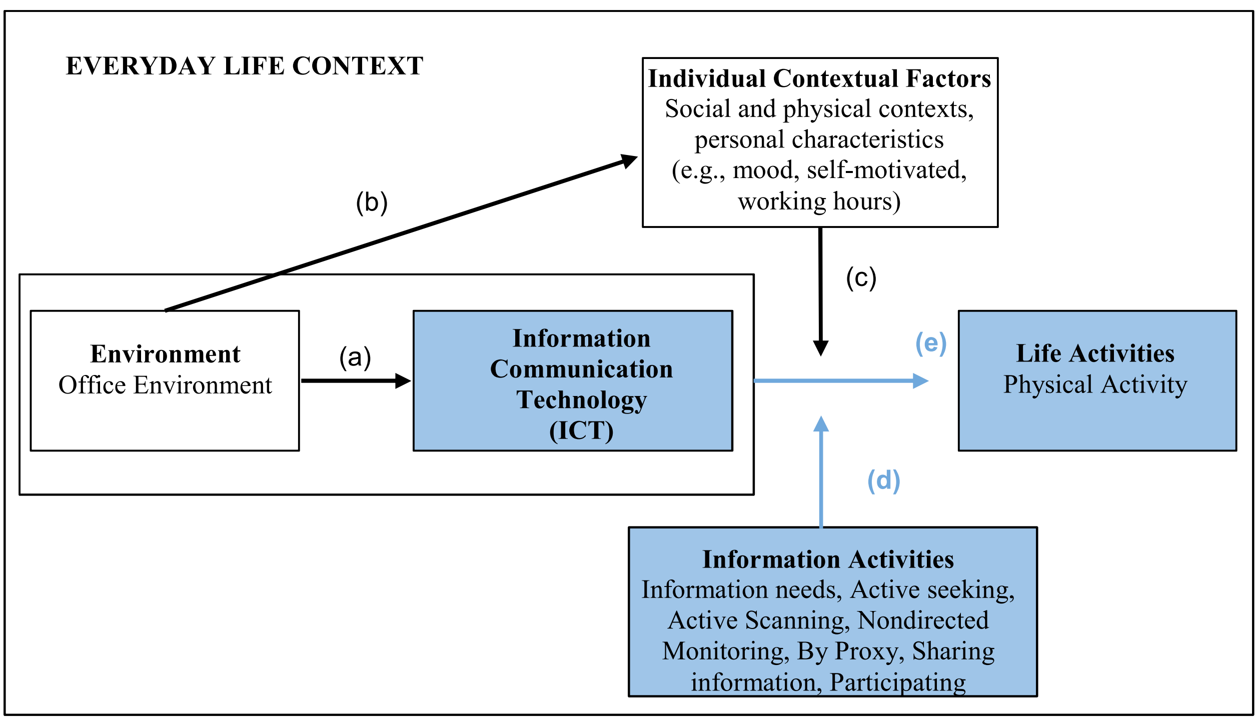


**Table 5.6 Information Practices Mode**

| Mode | Participant Description |
|---|---|
| Information Needs | ● The need for physical-activity-pattern information in everyday life |
| Monitoring | ● Monitoring physical activity data, including step counts, sleep, heart rates in everyday life, mainly to accumulate data |
| Active Seeking | ● Searching to find whether other people posted articles and reviews about wearable activity trackers (e.g., when they chose to buy a device)<br>● Searching to find whether there is information related to mobile applications that work with Fitbit or on firmware updates<br>● Searching to find information about what new devices came out and how other wearable activity tracker users were using them<br>● Information channel: Google discussion forum, YouTube |
| Active Scanning | ● Very few participants acted on the information practice of active scanning, which involves following friends' Fitbit data to see their daily steps (few participants did active scanning) |
| Nondirected monitoring | ● Few participants acted on the information practice of nondirected monitoring, which involves receiving information about exercise and wearable activity trackers by chance when reading posts on social media<br>● The main information channel for nondirected monitoring was Facebook |
| By Proxy | ● Few participants asked other people to find information for them about wearable activity trackers<br>● They did not directly ask people offline; instead they asked other people online to find information for them. |
| Sharing Information | ● Some participants used to share their tracking data with their friends and family using the Fitbit mobile app, text messages, or through their SNS (social network service)<br>● Some participants hesitate to share their information with others |
| Participating | ● Some participants participated in social networks or discussion groups to look for an online friend to compete with through the Fitbit app, or to find information related to new products<br>● Some participants did not participate in discussion or social network groups related to Fitbit |

As shown above, wearable activity tracker adopters' information practices of information needs, seeking, and monitoring were relatively strong. Otherwise, the information practices of active scanning, nondirected monitoring, monitoring by proxy, sharing information, and participating were relatively weak. It seems that participants were more interested in using the device to collect and monitor data individually, rather than sharing with or monitoring through others. Although users can share their own data and monitor their friends through Fitbit's friend list, the feature was not used frequently. Furthermore, the results showed that information activities correlated strongly with life activities. Therefore, it is important for designers to provide device functionality features in accordance with users' individual context and personalities.

### 5.3.5 Theme 5: Evolution of Life Activities (Physical Activity) in an Everyday Life Context via Wearable Activity Tracking Device Use (Figure 5.8, (e))

All of the participants cited below reported that they did not have time to exercise in daily life, so they tried to move more in daily life after beginning to use the devices. Life activities were changed based on environmental elements upon using the device. The process of **(e)** (Figure 5.3) describes how office workers' life activities changed after using the devices, and also what factors affecting life activities were needed to sustain use of the device. The following quotations from interviews match data from a pre-questionnaire in which I asked what type of physical activities participants typically perform to increase their step counts while they worked (on weekdays) and the results were as follows 1) Take a walk within the company (34.9%), 2) walk to the office when commuting (25.4%), and 3) use the stairs instead of the elevator (23.8%) (see Table 4.3). The following quotation also describes how the participants tried to find a way to walk more in daily life to reach the goal provided by the device:

1. *Participant (P13): I do not have time to exercise in the workplace. I should exercise after work, but I am tired of doing so* ***I tend to walk a lot during the day****.*
2. *Participant (P3): I do not spare time for exercise.* ***But, I walk when I commute****. I tried to add up the steps since I used this Fitbit.*

*3. Interviewer (Me): Do you usually just walk for your exercise?*

*Participants (P5): Yes, I check the step counts since I used this device. At lunchtime ... I really don't have to walk if not intentionally. Because my company and house are well-located, and the transportation is also well-developed. So normally, I can't reach 10,000 steps. In fact...* ***I go out for a walk during lunch time or walk to a far place to eat*** *for 6 or 7 thousand steps a day. I think it is motivating.*

*4. Interviewer (Me): So you started riding a bicycle when you commute? For exercise?*

*Participant (P9): I think there are largely two reasons. First, I tried to save transportation expenses. Second is to exercise...It is because I did few exercises... like going to the gym... but eventually, I ended up not going.* ***But commuting is something that you can't avoid,*** *so in order to both exercise and save some expenses, I started to ride a bicycle.*

*5. Participant (P15):I use the stairs instead of the elevator after lunch.*

*6. Participant (P1): Yes, whereas possible,* ***using stairs instead of elevators*** *when visiting other department [in the company] or else in the company adds up to exercise a bit by bit. I try to walk a lot and move a lot.*

*7. Participant (P17): Sometimes I intentionally take public transportation. I usually use a car when I go somewhere, but I realized that to get some more data and fill this (data), it is better to use public transportation rather than drive a car. So I tend to use public transportation a bit more now. Also, during break time, I intentionally tend to go to the break room (to walk more) rather than just sitting in my cubicle.*

As seen in the quotation above, participants who work in Korean companies as office workers do not make spare time to work out (actually, they do not have time to work out). However, they felt the need for exercise and found ways to introduce more physical activities into daily life using wearable activity tracking devices.

It is important to figure out users' environment, individual contextual factors, and information behaviors when we design such a device that lead to meaningful change. One of the example features from Fitbit that does not consider users' environment and contextual factors is the "Reminder to Move notification." This notification signals break time from sedentary activity. Most participants stated that it was useless, since it does not consider the workplace situation. The following quotations support that participants did not use the reminder to move notification, choosing instead to just turn it off.

> *1. Participant (P2): I turned that notification off. In fact, there are not many occasions that I can walk during the work hours. If you have a meeting or need to keep working, you cannot get up and walk even if you're notified.*

> *2. Participant (P5): I have not turned it off, but I think it does not motivate me to exercise. In fact, it is difficult to roam around in the company. Oh, it's the alarm, how long have I been walking? I see it when it alarms. But I do not get up and walk around.*

> *3. Participant (P17): I just turned it off. (Oh, why?) It alarms once every hour. So, it was quite bothering when I have to focus on something else [at work], so yes, I turned it off.*

Already, the goal-setting feature provided by Fitbit allows users to set their goals by themselves. These goals can be related to steps, exercise, or calories burned considering individual context. Each goal can be customized by the user through Fitbit's mobile app or website. Most of our participants set their step goals by themselves rather than using default (pre-set) goals. Participants' goals kept changing based on their individual context, such as self-efficacy—that is, the belief that individuals can achieve their goals (Locke and Latham 2002). The reason users changed their goals was often that a given default goal was too easy, so they set personal goals which were a little bit more difficult to achieve:

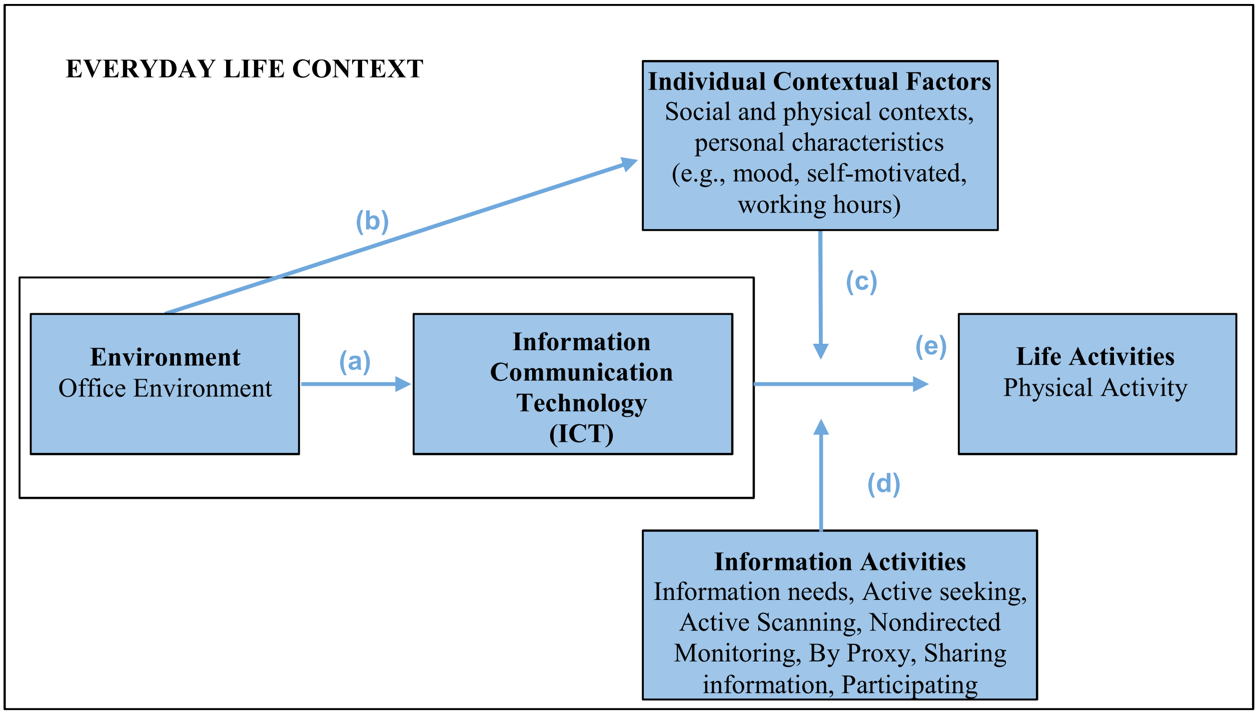
*1. Interviewer (Me): So you did not change your step goal, but kept it at 10,000 steps?*
*Participant (P13): There were times when I changed the goal upward or downward. Now it is 12,000 steps.*
*Interviewer (Me): Is 12,000 a number that you have set based on your daily average, or what you thought that you could reach without difficulty, or is there some other reason?*
*Participant (P13): I chose this goal because it's a little bit challenging, based on my abilities. Once, I set it as 10,000 and it was too easy to reach. So I adjusted it to 15,000, and I found that was too much for me. So now, I have it set it up as 12,000. I think the target needs to be something a little bit difficult to achieve. So I changed it to 120% of what I can do.*

*2. Participant (P19): At first I set the target as 8,000. Maybe the default was 8,000. Last week, I changed it to 10,000. I raised my step goal because I felt 8,000 was a bit too easy.*

This result aligned with previous evidence, as Locke's research asserted that "specific and challenging goals lead to higher performance than easy goals and 'do your best' goals"(Locke et al., 1981) p.125). Also, Locke stated that goals need to be specific and should be sufficiently challenging, but not too challenging.

Therefore, to facilitate continuous device use that could lead to positive change in life activity, any wearable ICT device needs to be customizable for an individual's context and environment.

**Figure 5.8 Highlited "Evolution of Life Activities (Physical Activity) in an Everyday Life Context via Wearable Activity Tracking Device Use"** ((a), (b), (c), (d), and (e) explain the interaction between the elements, and the arrow does not imply the sequence)




### 5.3.6 Theme 6: Life Activities That Changed After Using Wearable Tracking Device: How the Wearable Tracking Device Works as a Motivator (Figure 5.9, (e))

Based on analysis of research participants' interviews, the participants were divided into two groups. The participants in the first group were those who constantly used the devices because they were motivated by the wearable devices to exercise a little more (the device acted as a motivator to increase physical activity). This group considered the Fitbit to be a motivator for making them move more, which led to sustained use of the device. The following quotation indicates that participants changed their life activities (physical activities) after using the device since they were motivated by using it:

1. *Interviewer (Me): Are there any definite changes in the amount of activity or some kind of behavior before and after using this?*

*Participant (P9): I have much. I have exercised roughly and thought it would be enough. Now, I have definite goal. Let's just walk to make it 10,000 steps. Let's make 2,000 calories. That's why I am motivated. The motivation it gives me is enormous now.*

2. *Interviewer (Me): Is there any special event that makes you have passion to exercise?*

   *Participant (P10): After buying this Fitbit. It records my steps. It calculates the calories. I want to do a diet this time. If I eat something I have more exercise. That is my determination. I walk in free spaces in work places and try to walk more. Fitbit changed me like this.*

3. *Interviewer (Me): Did you exercise regularly before using this device?*

   *Participant (P2): Before this, I did not exercise everyday. I think I did once or twice a week. After using this device, I try to walk 20,000 steps to reach my goal that I've set it.*

4. *Interviewer (Me): What is the biggest change in behavior before and after using the device? For example a little more exercise or ...*

   *Participant (P13): Yes, that is true for me. More walking. When I can walk I try not to use a car but walk to the destination. That is the biggest change, I think***.**

The following quotations also indicate that participants considered the Fitbit a motivator to be more active because it provided objective numbers for physical activities such as step counts, calories burned, and heart rate for each user. If an individual was already motivated to lose weight or had an interest in their own health because of health problems (individual context), the wearable device became a great motivational tool.

1. *Participant (P12): I got motivated to increase my exercise after using this device. [Before I used this device] I usually exercised an hour and thought it would be enough. But when I use this [Fitbit] and check with calories, distance and amount of exercise that I did for an hour, it was less than what I thought. I should say it provides me the exact numbers that I could realize the reality. I think this part is good.*

2. *Participant (P16): After I use this device, sometimes I think I have to walk to achieve the goal of 10,000 steps. So it motivates me anyway. I cannot say it is 100% motivating, but it gives some motivation. Anyway it makes me walk a little longer. That is the biggest help that I got from the use of the device.*

3. *Participant (P17): Yes, the steps increased definitely. Before using the device, I used to use a car rather than walk. Therefore, I used to walk 2,000 steps until I finished work and went home. But now, when I leave the company, it's already over 6,000 to 7,000. As I wanted to walk more, I prefer public transportation rather than driving a car."*

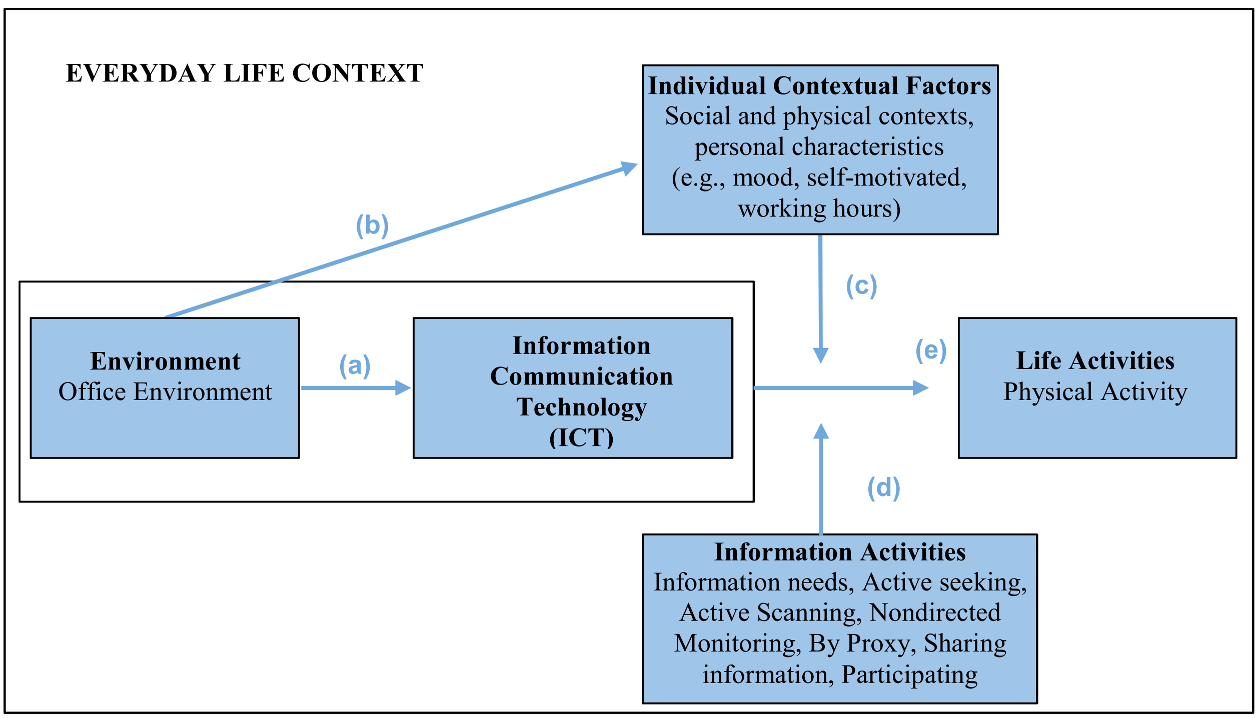
The second group consisted of participants who did not consider the device itself a motivator to be more active, but it provided physical activity data that motivated them to continue using it. This group became motivated by monitoring their physical activity information, rather than increasing their physical activity:

*1. Interviewer (Me): Didn't you get a lot of exercise after using this device?*
*Participant (P11): It's not like that. This is for the purpose of monitoring and confirming my data when exercising. It's not a motive for more exercise.*
*Interviewer (Me): That means the device is not motivating you to exercise more, right?*
*Participant (P11): Right, I just check the information. For example, when I jogged I usually monitored how much I ran where I ran.. I was interested in such data.*

*2. [The reason I'm using this device is] rather than increasing my activities on a daily basis, I am concentrating on what I do and I want to keep a record of my workouts.*

Users either derived motivation from the Fitbit (by monitoring the data) or increased physical activity was reinforced by the device. If a user satisfied one of these two conditions, the device was used continuously. As in the above interview transcripts, if information-seeking motivation was strong and individual contextual factors fit well with the user, then the device motivated the user enough for sustained use. This led to more physical activity, and positive changes in life activities.

**Figure 5.9 Highlighted "Life Activities That Changed After Using Wearable Tracking Device: How the Wearable Tracking Device Works as a Motivator"** ((a), (b), (c), (d), and (e) explain the interaction between the elements, and the arrow does not imply the sequence)



### 5.3.7 Theme 7: Suggestions Based on Analysis of Adopters' and Abandoners' Use of the Wearable Activity Tracking Device (Figure 5.10, (e))

One of the major reasons abandoners stopped using their devices was this: Participants reported that since they are office workers, they were hard-pressed to find spare time for exercise. Then, they lost their interest in exercise, which led to abandonment of device use. However, all of the adopter participants also reported that they did not have time for exercise in daily life, but still tried to find ways to move more in daily life, such as 1) taking a walk within the company facility, 2) walking to the office when commuting, or 3) using the stairs instead of the elevator. EMA results also support when the participant used stairs instead of elevators, it had a positive interaction with the number of steps (see Table 5.2).

Abandoners also pointed out they abandoned their device since the information provided by the device is not useful. They mentioned that data were very similar in pattern every day. Meanwhile, adopters preferred to collect their data by using the device and they asserted that the act of accumulating data was important to them. Even though they knew that there was no significant change in movement data in their everyday lives, they tried to collect data and felt the data to be more valuable than non-adopters it. Abandoners felt that it would be better if the device provided more meaningful analysis instead of simply raw data.

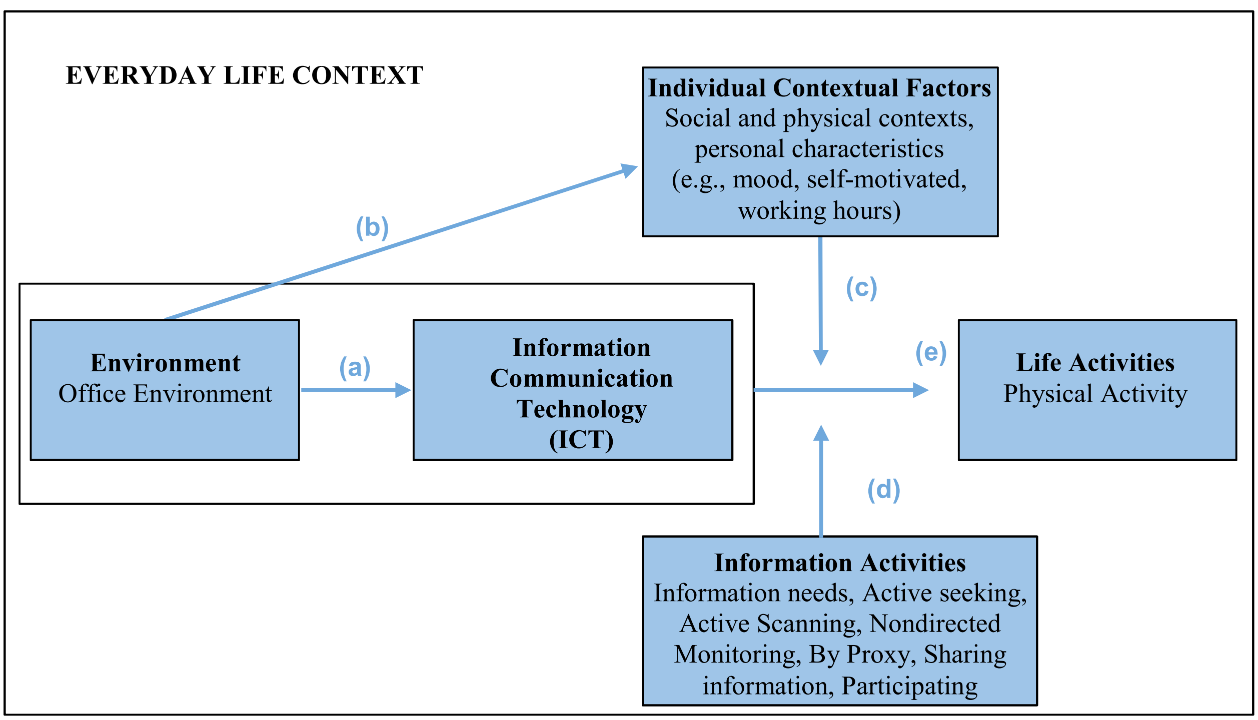
Another difference between adopters and abandoners was that abandoners thought the fitness-focused Fitbit device was too simple, and that the accuracy of measured data was not that correct. These participants wanted more functions, like those provided by smartwatches. Otherwise, adopters liked to use the fitness-focused Fitbit device rather than using smartwatches, since they sought simplicity in their devices.

*Interviewer (Me): Have you ever thought about using a smartwatch?*

*Participant (P8): I wore a watch for a while, but it was heavy. I do not usually wear watches. Fitbit is about fitness-focused devices. A smartwatch has more than that, so I do not need it. I do not need the feature to make a call that's provided by a smartwatch, so I am happy with the use of a Fitbit.*

*Participant (P1): The first [good] thing is that it [Fitbit] is convenient to use… Other things such as smartwatches are heavy and their batteries do not last long. The Fitbit device is light, but the battery lasts a long time. It has all the features that I want. Apple Watch and similar things have many other features, and I think those features are not necessary for me to do exercise. Therefore, I decided to have this [Fitbit].*

**Figure 5.10 Highlighted "Information Activities , ICT, Life Activities, Individual Contextual Factors, and Environment" to explain differences between adopters and abandoners** ((a), (b), (c), (d), and (e) explain the interaction between the elements, and the arrow does not imply the sequence)



**To better support wearable activity trackers, system designers should consider users' environments, individual contextual factors, and information practices. Based on the results, I suggest the following design recommendations:**

First, a small sample of potential daily tasks could be considered physical activity, so devices need to provide guidance for the types of movement that can be done in daily life (such as using stairs instead of elevators) rather than focusing on actual exercise. Wearable ICT devices need to be considered based on individual context and provide suggestions for physical activity that could be done in everyday life based on their environment.

Second, all the self-tracking data from different brands of wearable activity tracking devices need to be integrated into one platform. For example, adopter P14 used Fitbit and wanted to change different brands of wearable activity tracking device, but didn't change it because he was afraid of losing his previous self-tracking activity data. Self-tracking data from different brands of devices could be interchangeable based on each user's profile. Although the users want standardization of all the data they collect, wearable activity tracker companies probably wanted siloed environment so they can lock users into their products.

Third, the devices need to provide more meaningful data analysis. Abandoners stated that merely collecting and viewing data was not enough to keep them interested in using the device. They wanted to get more elaborate analysis based on the collected data—for example, providing a service that could connect a sleep expert (consultant) with users' sleep data. One adopter, P2, mentioned that he wanted to have access to a service that would allow his data to be analyzed:

> *Participant (P2): I am still monitoring the health aspect of the sleep analysis. I would like to have a service that can connect me to experts with [sleep] data.*

Fourth, my research proved that participants mainly did very *light* level of physical activity (sitting in the office) in the morning, and were found to walk less -1309.75 steps counted ($p<0.01$), while people who reported they performed the activity level of *moderately vigorous plus* walked more by 9837.66 ($p<0.01$) (see Table 4.9). People who reported they did the activity level of *vigorous* activity walked 7328.83 ($p<0.01$) more (see Table 4.9). These results illustrate that sitting in an office has a significant interaction with the number of steps taken by research participants. On the other hand, *moderately vigorous plus* and *vigorous* levels of physical activity show around 10,000 more steps, which is a huge difference. Therefore, devices need to provide more detailed information about the intensity of physical activity following well-established exercise guidelines, and show how intensity of physical activity relates to increased step counts. Therefore, this could provide personalized intensities of physical activity guide to users.

Fifth, based on my analysis, any wearable ICT device must be customizable and personalized for a user's context and environment. AI (Artificial Intelligence)-based trackers might make this possible by collecting and transforming raw data into insightful suggestions and recommendations for users. For instance, an AI-based tracker might learn a user's daily schedule and recognize by time or location when a user is going to another location at work they would be encourage to take the stairs to another floor instead of the elevator. As another example, an AI-based tracker could change step goals and suggest alternative physical activities that could be best fit a given day based on the user's schedule, location, or even the weather. An AI based trackers possibly could this by analyzing many streams of contextual information and then providing a tailored plan that can lead to more effective physical activity in the user's daily life. Here are the specific examples of how device could customize:

- Suggest kind of exercise users can improve in some location.
    - If user was waiting for elevator, device possible could send a message like "you can use stairs instead of elevators"

    - Users who prefer to workout outside and if it raining outside or snowing, device could send a message like “use gym or do indoor activities”
    - During a work time, if user do not many occasions that they can walk during the work hours, provide some activity guidelines that can be done during sitting in the desk (e.g., stretching)
- Provide real time coach
    - If user set goal of steps (150 steps) per minute and when user jogging pace is too slow (less than 150 steps per minute), AI devices prods user that user need to increase steps per minute.
    - If user heart rate is too high (seems like user got a lot of stress), AI provide some message like “you can deep breath to relieve your stress” or play calm music that help user to relieve their stress.
- Consider user’s schedule and calendar
    - When user attended in the meeting, all the regular notifications will be turned off to make user concentrated on their meeting.

This is evidenced by participant 4, who commented that Fitbit does not help personalize plans to make the data more meaningful:

> Interviewer (Me): *Do you think these data will only be meaningful in the present or that it will be useful in the future?*
> Participant (P4): *Well, actually, I think the current step data provided by Fitbit do not make much sense. I’m monitoring and collecting data for now, but the data do not give me any more information. I hope Fitbit provides users more personalized data and functions rather than just giving users the actual number of steps. For example, if I’m tired one day, I want to be able to*

*combine the physical activity data with weather and temperature data at that time to let me find out why I'm feeling so tired.*

Last, here are several technical aspects that all participants mentioned: 1) increase accuracy so that the device could be less sensitive (does not count the steps when user is only using their hand). 2) want to collect more different data types of physical activity; for example, if users play tennis, the device could calculate the correct step counts, 3) waterproofing does not work well, so increase waterproof function, and 4) make battery life last longer, so losing data by battery drain is no longer a concern.

### 5.4 Research Questions and Summarization of Results

In this section, I addressed the research questions in light of all the results. Initially, I had three research questions through a mixed-method approach using office workers as the population and having them utilize wearable activity trackers. The first research question was:

*What contextual factors (social and physical environments and personal characteristics [e.g., self-motivation]) interact with physical activity in everyday life when incorporating the use of wearable activity trackers?*

To explore Research Question 1 with wearable activity-tracker adopters (participants), EMA data, pre-interview survey data, Fitbit log data, and interview data are included to discover integral contextual factors in their daily lives in an office setting. I discovered integral contextual factors where physical activity in everyday life such as mood, total working hours per day, and level of stress in the use of wearable devices interact in everyday life. Chapter 5.1 and Chapter 5.3 describe the answer for the Research Question 1.

For example, a person's stress level reported through morning EMA has a statistically significant interaction with the moderate-intensity level of physical activity of the day. As stress increased, a negative interaction with activity minutes of moderate-intensity level (fairly active) was observed. My EMA data analysis results indicate that ‘total working hours per day is also one of the contextual factors that negatively interaction with moderate-intensity physical activity. As the total working hours increase, a negative interaction with activity minutes of moderate-intensity level(fairly active) was observed.

Among the contextual factors that I discovered, I found the work/social environment to be the most significant factor to negatively affect physical activity practices. Long working hours and having lots of stress from work also affected physical activity negatively. Otherwise, social connections were the least important factor among my participants.

In the model, the relationship between (c) and (e) describes how the individual contextual factors affect life activities in the use of a wearable activity-tracking device that shows the answer of Research Question 1.

The second research question was: *What information practices (information-seeking, using, and sharing) can be identified in the context of the office workers who incorporate the use of wearable activity trackers in everyday life?*

To explore Research Question 2 with wearable activity-tracker adopters (participants), EMA data, pre-interview survey data, and interview data are included to identify information practices of those who incorporate the use of wearable activity trackers in everyday life. In Chapter 5.3.4, interview data was coded and focused on categories relating to McKenzie’s model to provide a discussion of information activities that affect life activities (physical activity) in the use of the wearable activity-tracking device.

According to my results, wearable activity-tracker adopters’ information practices of needing, seeing, and monitoring information were relatively strong, but the information practices of active scanning, nondirected monitoring, monitoring by proxy, sharing information, and participating were relatively weak. For example,  my research participants (wearable device adopters) started to use the device to obtain information on physical-activity patterns in everyday life based on their needs (information practices of needing). Based on the McKenzie questionnaire, most participants (27 adopters) reported that they were often (n = 12, 44.4%) and regularly (n = 11, 40.7%) in need an information about physical activity and wearable activity trackers (Fitbit) or felt as if they should know more about them.

Also, my research participants had a great deal of data accumulation as a result of monitoring their physical activities—step counts, sleep, and heart rates in everyday life (information practices of monitoring information). They also mentioned that collecting and accumulating data were the major reasons for continuing to use the device. Consequently, the data suggest that it is critical to understand information needs and practices in everyday life when using an information system, such as a wearable activity tracker, to see how needs and information practices impact personal activities. Therefore, this study asserts that it is important for designers to provide device functionality features in accordance with users' individual contexts, personalities, and information need.

Those were described in the relationship between (d) and (e) in the model.

The third research question was: *What are the differences between adopters and abandoners of wearable activity trackers, how are their motivations different, and what makes them keep using or abandon the device?*

To conduct Research Question 3 with wearable activity-tracker adopters and abandoners, interview and survey data are included to examine why users adopt or abandon activity trackers and to identify the possible cause of abandonment.

At first, reasons for device use motivation were similar among both adopters and abandoners. Although the motivation for using the Fitbit was very similar among the two populations, abandoners stopped using the device after some use (less than 1 week to more than 2 years, see Table 4.23). The most common reason to start using the device reported by abandoners was "to get to know myself better by using the device" (41.53%, see Figure 4.1). Similarly, but slightly different from abandoners, adopters' motivation for beginning device usage was getting to know themselves better by using the device, especially among those who wanted to check their existing life patterns, such as how much they walked in daily life. Abandoners were more interested in exercise than in everyday life patterns. They wanted to increase exercise by using the wearable device.

One of the differences I discovered is that abandoners pointed out that the information provided by the device is not useful. They mentioned that the data were very similar in pattern every day. Meanwhile, adopters preferred to collect their data by using the device, and they asserted that the act of accumulating data was important to them. Even though they knew there was no significant change in movement data in their everyday lives, they still tried to collect data and felt that the data were more valuable than the non-adopters did.

In the model, (a), (b), (c), (d), and (e) describe how a wearable tracking device works as a motivator that causes a user to sustain using the device. Users either derived motivation from the Fitbit (by monitoring the data) or increased physical activity was reinforced by the device. If a user satisfied one of these two conditions, the device was used continuously. If information-seeking motivation was strong and individual contextual factors fit well with the user, then the device motivated the user enough for sustained use. This led to more physical activity and positive changes in life activities.

The more detailed description is described in Chapters 5.3.6 and 5.3.7.

## 5.5 Generalization

If I were to study different populations, such as non-office workers or farm workers in Mexico, the possible integral individual contextual factors will differ from those of the office workers. This is why I developed a model like Figure 5.3 to generalize my study.

For example, the work environment of farm workers in Mexico is outside (field) most of the time. Previous studies have indicated that farming is physically demanding, but machinery and vehicles assist with a lot of physical work, so farmers spend a lot more time sitting than walking, which is linked to obesity (Pickett et al. 2015). This work environment affects individual contextual factors, such as level of physical activity. Also, they try to find a way to do more physical activity (or check their physical activity patterns) in daily life, so farmers could start using wearable activity trackers. Also, farmers could try to find ways to do more physical activity in their daily routine, such as by walking down to check the livestock (animals) instead of using a quad bike. Life activities can change based on individual contextual factors and the environment.

Significant individual contextual factors can vary depending on the type of population, but the environment's impacts on individual contextual factors, life activities that changed after using a wearable tracking device, and information activities that affect life activities in the use of wearable activity monitors can be explained by this developed model.

# CHAPTER 6: CONCLUSION AND FUTURE WORK

## 6.1 Conclusion and Contribution

This dissertation seeks to discover how the context of office workers' everyday life relates to the physical activity of steps taken during the day as measured through the use of wearable activity-tracking devices. Few studies stress the roles of individual and contextual factors and how these affect physical activity incorporating the use of activity-tracking devices in daily life. By using the mixed-method approach, including in-depth, semi-structured interviews and questionnaire assessments, supplemented with the novel EMA (daily diary) data collection method and activity log data, this study discovered integral contextual factors that could influence physical activity changes incorporating the use of wearable devices in everyday life.

Based on the descriptive results and statistically significant interaction results, the study found integral contextual factors (e.g., mood, total working hours per day, level of stress) that could influence physical activity changes in the use of wearable devices in everyday life. Few studies stressed the role of individual contextual factors in physical activity (McNeill et al. 2012; Lo et al. 2015; Schüz et al. 2012), but these do not consider how those factors affect physical activity incorporating the use of activity-tracking devices in daily life. Therefore, this study fills the gap in our knowledge about the role of contextual factors and how these affect physical activity in the use of wearable activity-tracking devices□that could be used for system designers who are designing such a wearable activity tracker.

Furthermore, this dissertation reveals information about the practices of office workers in everyday life by incorporating the use of wearable devices based upon McKenzie's(McKenzie 2003) and Hektor's(Hektor 2001) information practices theory. According to the results, wearable activity tracker adopters' information practices of needing, seeking, and monitoring information were relatively strong. On the other hand, the information practices of active scanning, nondirected monitoring, monitoring by proxy, sharing information, and participating were relatively weak.

During an interview, one of participants competed with her husband using some of the offered features and stated that she checked his steps taken during the day. If she realized that she had fewer steps than him, she tried to take more steps during and after work. However, for the most part, the results show that participants were more interested in using their device to collect and monitor data individually rather than share with or monitor others. Consequently, the data suggest that it is critical to understand information needs and practices in everyday life when using an information system, such as a wearable activity tracker, to see how needs and information practices impact personal activities. Therefore, this study asserts that it is important for designers to provide device functionality features in accordance with users' individual contexts, personalities, and information needs. Current ICT can only help in some situations; for example, people were motivated to exercise the most when experiencing light to moderate stress. But others did not exercise as much when highly stressed or happy. This means that an AI-based tracker or "smart" ICT could potentially recognize contextual information and encourage healthy behavior (exercise) in situations (high stress or happy) in which the user would not tend to exercise otherwise. An AI-based device could potentially engage users more and could encourage healthier behaviors through personalized recommendations by providing a tailored plan that can lead to more effective daily physical activity in the user's life.

Furthermore, a two-phase study was conducted to examine why users adopt or abandon wearable activity trackers. The two-phase study included two specific populations of 27 adopters (for phase 1) and 66 abandoners (for phase 2) to examine the differences in the use and adoption of the devices. Based on the results of two populations, I discovered differences and suggested guidelines for the designers of wearable activity trackers: 1) wearable ICT devices need to be considered based on individual context and need to provide suggestions for physical activity that can be done in everyday life based on the user's environment, 2) self-tracking data from different brands of wearable activity-tracking devices need to be integrated into one platform, 3) the devices need to provide a more meaningful data analysis, and 4) the devices need to provide more detailed information about the intensity of physical activity following well-established exercise guidelines and show how the intensity of physical activity relates to increased step counts.

Based on deductive and inductive processes, this dissertation proposes an everyday life information behavior model that describes the relations between five elements: environment, ICT, contextual factors, information activities, and life activities. In this study, information activities (information practices) are classified differently from life activities (everyday behaviors) and described differently in terms of how they affect each other. Also, the model describes how the environment affects technology use and how the use of a device begins, depending on the environment. The study suggests that understanding the environment is key to designing better information technology that leads to meaningful behavior changes. The model suggests that it is important to understand what the information needs and contextual factors are for information system users to achieve better information flow and to design better systems that lead to meaningful behavioral changes. Additionally, to facilitate continuous device use that could lead to positive changes in life activity, any wearable ICT device needs to be customizable for an individual's context and environment. The model emphasizes that it is important to figure out users' environments, individual contextual factors, and information behaviors when designing such a device that leads to meaningful change.

The findings presented in this dissertation add to our theoretical understanding of everyday life information practices. This also has practical implications for systems designers of wearable activity trackers, who should consider users' environments, individual contextual factors, and information practices.

### 6.2 Limitations of Study

This study has several limitations. This study sample population was a group of people who already participate in social networks such as the Fitbit online community, and was very familiar with using technology. This group will be comfortable with technology and more positive about using health technology and devices, so participants would have had more experience and interest in technology in general than other groups of people, which could lead to the possibility of biased results. Aligning with this, because the study have investigated the specific environment of office workers in Korean company culture, this study might not be applicable in a more general environment and also it could be different in other occupations. Furthermore, the interview questionnaires and diaries used in the study rely on the self-report format and the survey method. Questions may be interpreted differently by respondents; this also applies to the study.

### 6.3 Reflection of Study

One of the main concerns in conducting this study was data collection. I thought that this would be the primary limitation of my study. I conducted three data collection phases, my research participants (adopters) were required to provide a qualitative interview and Fitbit data, and write Ecological Momentary Assessment data (diaries) twice per day for five days. My concern was whether users were participate fully in this study with little compensation. I was also worried whether participants would provide their diaries twice a day. Interestingly, adopters who kept using their devices and were interested in their wearable activity tracker were eager to participate, and provided all the data that I collected, fully participating in the study with little compensation. Since participants had contacted me with their willingness to participate in this study by responding to a recruitment letter, there was no one who dropped out of the research during the full research period. There were a few participants who forgot to provide EMA diaries within a given time, so I sent a text reminder to fill it out that lead to a 100% response rate. Some research participants were willing to participate even though they did not know that they would receive any compensation.

On the other hand, I thought that recruiting abandoners (who might participate in the short survey and sell their devices online on the secondary market) would be much easier than recruiting adopters. However, they did not have a willingness to participate in the study at first. Since I contacted them individually by text message to introduce the study and ask if they were willing to participate, many thought it was text message scam. Therefore, it was difficult to recruit abandoners, even though they only needed to participate in a short online survey compared to adopters' data collection requirements. Due to these factors, I had to contact a lot of people. Sometimes I did not get an answer, and sometimes I had a message asking me to stop sending messages. It took a lot more time to recruit adopters than I expected. I realized that when recruiting participants, their willingness was most important in conducting research, regardless of the population.

### 6.3 Future Study

Based on the results of this research, this study provides several agendas for future study. First, one of the directions is to consider how the results from this study apply to other occupations in different cultures. In this study, the environment is an office setting in Korea where as an everyday context office workers sit all day at desks using computers. These factors affect participants' physical activity levels and individual context factors in daily life, which was mostly spent being sedentary during work hours. This study might not be applicable in a more general environment, and the results also could be different for other occupations. Therefore, to generalize this study's results, future research should be considered, such as conducting a study with different cultures (e.g., office workers in different countries) or other occupations to see how the environment affects individual factors and participants' physical activity incorporating the use of wearable activity trackers.

In line with the above suggestion of future research, this study's participants were very familiar with using technology. The group in this study tended to be more comfortable with technology and more positive about using health technology and devices, so the group would have had more experience with and interest in technology in general than some other groups of people. Future research needs to be continued in populations who are less familiar (e.g., the older people) with using technology to explore how and whether those populations keep using or abandon wearable activity trackers.

Another important direction is to consider increasing the reliability of the EMA data collection method. A key concept that must be considered is that EMA assessments represent a sample of the participants' experiences. They are capturing data about the person's full range of experiences in one fell swoop. For example, in this study EMA collection was done with 27 adopters during fall (September to November). During this season in Korea, the weather is mostly nice for exercising outside or walking to work when people commute. However, winter (usually December to March) in Korea is mostly snowy and extremely cold, which could affect people's physical activity styles and patterns. During an interview, my participants also stated that they preferred to walk to work during nice weather. But the winter is mostly snowy and extremely cold, so that could affect people's physical activity styles and patterns, such as doing less physical activity and having a lower average level of steps, or trying to find more indoor activities to increase their steps. I might see less impact and significance of some factors if I repeated the study in the dead of winter. That is why I developed the mode shown below to generalize my study. For example, environmental factor—winter—affect individual contextual factors (e.g., less motivated to work out or mood) that affects activity in daily life.

To increase the reliability of EMA, future research needs to be continued using the EMA method to collect participants' contextual and environmental factors in different seasons. This would show how environmental factors affect people's patterns of physical activity and how people try to find ways to increase their physical activity.

In conclusion, this research has contributed to a better understanding of how contextual and environmental factors interact with the physical activity of people who use wearable activity trackers. The research findings have practical implications for designers of wearable activity trackers. The study results also guide future research agendas.

## APPENDIX A. PRE-QUESTIONNAIRE

**Pre-interview questionnaire: survey on the office workers' daily use of Fitbit**

1. Please indicate your age.

2. What is your field of work?
    a. Finance
    b. Information Technology (IT)
    c. Medicine
    d. Education
    e. Other

3. What is your gender?
    a. Women
    b. Men

4. Are you married?
    a. Yes
    b. No

5. Where is your workplace?
    a. Seoul
    b. Busan
    c. Daegu
    d. Daejeon
    e. Gwangju
    f. Other

6. How long have you been working at your current job? (i.e., 3 years)

7. How many hours do you typically work in a week?
a. Less than 40 hrs
b. 40 - 44
c. 45 - 49
d. 50 - 54
e. 55 and more

8. What is your educational background?
a. High school graduate
b. College/University graduate
c. Master's degree or above
d. Doctoral degree or above

9. How much physical activity (walking, running, working out) do you perform each day?
a. Less than 15 mins
b. 15 mins - less than 30 mins
c. 30 mins - less than 1 hr
d. 1 hr - less than 2 hrs
e. 2 hrs - less than 3 hrs
f. More than 3 hrs

10. What are your favorite physical activities?
a. Very Light (e.g., reading, standing, talking, sitting in office, studying)
b. Light (e.g., walking at a slow pace, light office work)
c. Light Plus (e.g., walking downstairs, cooking, shopping)
d. Moderately Vigorous (e.g., weight lifting, aerobics, walking on job)
e. Moderately Vigorous Plus (e.g., swimming, tennis, dancing)
f. Vigorous (e.g., hiking, skiing, jogging)

11. Please select all physical activities that you typically perform while you work (weekday) (**Multiple selections allowed**).
a. Walk to the office when commuting
b. Go to the gym to workout
c. Use stairs instead of elevators
d. Participate in exercise programs at work
e. Take a walk in the company
f. Other

12. Which biometric data did you measure with the device? Which data did you take an interest? (**Multiple selections allowed**)
a. Steps
b. Heart Rate
c. Distance
d. Calories
e. Sleep
f. Other

13. On average, how satisfied are you with your usual number of steps (provided by Fitbit)?
a. Very satisfied as I walk enough
b. Regretful for not reaching the desired target
c. Passable
d. I have no idea
e. Other

14. Please rate the level of stress that you receive at work in the scale of "1 - do not take stress at all" to "5 - get stressed the most"?

a. 1
b. 2
c. 3
d. 4
e. 5

15. How long have you used a healthcare wearable device?
a. Less than 1 week
b. Less than 1 month
c. Less than 3 months
d. Less than 6 months
e. Less than 1 year
f. Less than 2 year
g. More than 2 years

16. When you first started using the device, how did you perceive your fitness status and exercise?
a. I am not physically active, and I don't plan on doing any physical activity in the near future
b. I am not active at the moment, but I am thinking about being more active
c. I am preparing to do more activity and intend to start in the next month
d. I have been physically active for less than 6 months
e. I have been physically active for more than 6 months

17. Please indicate when you started using Fitbit (i.e., May 2016).

18. Please select one that best describes your confidence in using health technology devices such as wearable devices.
a. It is generally easy for me to use health devices (wearable devices)
b. Using wearable device is not easy, but I can use it in an appropriate manner
c. Using wearable device is not comfortable
d. I worry that I might break the device when in use

**The following is an evaluation form for your interest in usual exercise data and information regarding Fitbit device. Please rate each items below in the scale of "1 - Never" to "5 – Regularly".**

1. "*I am interested in information concerning physical activity (PA) and wearable activity tracker (Fitbit) or feel like I should know more about it*."
a. 1
b. 2
c. 3
d. 4
e. 5

2. "*I have been searching to find whether other people posted articles about wearable activity tracker and to find whether there was a discussion group/forum page about wearable activity tracker.*" 

a. 1
b. 2
c. 3
d. 4
e. 5

3. *"I'm following friends' Fitbit to see his/her daily steps and I'm following information about activity tracking devices."* □

a. 1
b. 2
c. 3
d. 4
e. 5

4. "I receive information about exercise and wearable activity tracker by chance when reading friend's post on social media and by chance from other people."

a. 1
b. 2
c. 3
d. 4
e. 5

5. "I have asked other people to find me information about exercise and wearable activity tracker."

a. 1
b. 2
c. 3
d. 4
e. 5

6. *"I have been sharing my tracking data with friends or I have been posting my tracking data on social media."*

a. 1
b. 2
c. 3
d. 4
e. 5

7. *"I'm participating in social networks or discussion groups related to wearable activity tracker."*

a. 1
b. 2
c. 3

d. 4
e. 5

**Thank you for your reply!**

## APPENDIX B. ECOLOGICAL MOMENTARY ASSESSMENT MORNING QUESTIONNAIRE

**Survey on the office workers' daily use of Fitbit – Morning**

1. What were you doing right before you started this survey? (i.e., commuting, having meals, working on computer, etc.)

2. Did you arrive at work?
a. Yes
b. No
c. I am on my way to work

3. Which of the public transportation did you take when you headed to work this morning?
a. Bus
b. Subway
c. Bus + Subway
d. Bicycle
e. On foot
f. Other

4. How do you feel now? (Multiple selections allowed)
a. Good
b. Joyful
c. Nervous
d. Tired
e. Depressed
f. Annoyed
g. Upset
h. Other

5. Please rate your current stress level in the scale of "1-very low" to "5-very high".
a. 1
b. 2
c. 3
d. 4
e. 5

6. Have you checked your data from Fitbit this morning? If so, how many times have you checked?
a. No
b. Yes, once
c. Yes, twice
d. Yes, more than 3 times

7. In what way did you check your data? (**Multiple selections allowed**)

a. Via Fitbit device
b. Via Fitbit's mobile app
c. Via PC

8. If you checked the data this morning, which data was it? (**Multiple selections allowed**)
a. Steps
b. Heart Rate
c. Distance
d. Calories
e. Sleep
f. Other

9. How did you feel when you checked the data provided by Fitbit?
a. It motivates me a lot
b. It motivates me a little
c. It does not motivate me at all
d. I have no idea
e. Other

10. What level of physical activity did you do this morning?
a. Very Light (e.g., reading, standing, talking, sitting in office, studying)
b. Light (e.g., walking at a slow pace, light office work)
c. Light Plus (e.g., walking downstairs, cooking, shopping)
d. Moderately Vigorous (e.g., weight lifting, aerobics, walking on job)
e. Moderately Vigorous Plus (e.g., swimming, tennis, dancing)
f. Vigorous (e.g., hiking, skiing, jogging)

11. How long do you think you have walked so far today? (Please write it down as you feel without checking the data on the device)

12. Please select all physical activities that you did this morning from below (**Multiple selections allowed**)
a. Walk to the office when commuting
b. Go to the gym to workout
c. Use stairs instead of elevators
d. Participate in exercise programs at work
e. Take a walk in the company
f. Other

13. Please check the Fitbit device and write the current number of steps

14. Please check your Fitbit device and write your current heart rate.

15. How is the weather now?

a. Clear
b. Cloudy
c. Raining a little
d. Raining heavy
e. Extremely cold
f. Other

**Thank you for your reply!**

## APPENDIX C. ECOLOGICAL MOMENTARY ASSESSMENT EVENING QUESTIONNAIRE

**Survey on the office workers' daily use of Fitbit – Evening**

1. What were you doing right before you started the survey? (i.e., leaving work, having a meal, doing house work, working on computer, etc.)

2. Did you leave work?
a. Yes
b. No
c. I'm leaving work now

3. If you are yet to leave work, what time are you going to leave? (i.e., 8 o'clock)

4. How do you feel now? (**Multiple selections allowed**)
a. Good
b. Joyful
c. Nervous
d. Tired
e. Depressed
f. Annoyed
g. Upset
h. Other

5. How many hours did you work today?
a. 8 hours
b. 9 hours
c. 10 hours
d. 11 hours
e. 12 hours
f. More than 13 hours

6. How long have you been sitting all day today?
a. 5 hours
b. 6 hours
c. 7 hours
d. 8 hours
e. 9 hours
f. More than 10 hours

7. Please rate your stress level today in the scale of "1-very low" to "5-very high".
a. 1
b. 2

c. 3
d. 4
e. 5

8. Please select all the data you have checked today
a. Steps
b. Heart Rate
c. Distance
d. Calories
e. Sleep
f. Other

9. How many times have you checked your data via Fitbit device display today?
a. I did not check the data via Fitbit device today
b. Once
c. Twice
d. 3 times
e. 4 times
f. More than 5 times

10. How many times have you checked your data via Fitbit mobile app today?
a. I did not check the data via Fitbit mobile app today
b. Once
c. Twice
d. 3 times
e. 4 times
f. More than 5 times

11. How many times have you checked your data via Fitbit website (on PC)?
a. I did not check the data via Fitbit website today
b. Once
c. Twice
d. 3 times
e. 4 times
f. More than 5 times

12. Did you compete with your Fitbit friends via Fitbit app today?
a. Yes
b. No

13. What level of physical activity did you do this evening? (**Multiple selections allowed**)
a. Very Light (e.g., reading, standing, talking, sitting in office, studying)
b. Light (e.g., walking at a slow pace, light office work)
c. Light Plus (e.g., walking downstairs, cooking, shopping)

d. Moderately Vigorous (e.g., weight lifting, aerobics, walking on job)
e. Moderately Vigorous Plus (e.g., swimming, tennis, dancing)
f. Vigorous (e.g., hiking, skiing, jogging)

14. How long do you think you have walked so far today? (Please write it down as you feel without checking the data on the device).

15. Please select all physical activities that you did this today from below (**Multiple selections allowed**).
a. Walk to the office when commuting
b. Go to the gym to workout
c. Use stairs instead of elevators
d. Participate in exercise programs at work
e. Take a walk in the company
f. Other

16. Please check the Fitbit device and write the current number of steps.

17. Please check your Fitbit device and write your current heart rate.

18. How is the weather today?
a. Clear
b. Cloudy
c. Raining a little
d. Raining heavy
e. Extremely cold
f. Other

**Thank you for your reply!**

## APPENDIX D. QUESTIONNAIRE FOR ABANDONERS

**Survey on the disuse of wearable activity tracker in everyday life of office workers**

1. Please indicate your age.

2. What is your field of work?
 a. Finance
 b. Information Technology (IT)
 c. Medicine
 d. Education
 e. Other:

3. What is your gender?
a. Women
b. Men

4. How long have you been working at your current job?
a. Less than 1 year
b. 1 - 4
c. 5 - 9
d. 10 - 14
a. 15 years and over

5. How many hours do you typically work in a week?
a. Less than 40 hours
b. 40 - 44
c. 45 - 49
d. 50 - 54
e. 55 - 59
f. 60 - 64
g. 65 - 69
h. More than 70 hours

6. How much physical activity (walking, running, working out) do you perform each day?
a. 15 mins - less than 30 mins
b. Less than 15 mins
c. 15 mins - less than 30 mins
d. 30 mins - less than 1 hr
e. 1 hr - less than 2 hrs
f. 2 hrs - less than 3 hrs
g. More than 3 hrs

7. What are your favorite physical activities?

a. Very Light (e.g., reading, standing, talking, sitting in office, studying)
b. Light (e.g., walking at a slow pace, light office work)
c. Light Plus (e.g., walking downstairs, cooking, shopping)
d. Moderately Vigorous (e.g., weight lifting, aerobics, walking on job)
e. Moderately Vigorous Plus (e.g., swimming, tennis, dancing)
f. Vigorous (e.g., hiking, skiing, jogging)

8. Please select all physical activities that you typically perform while you work (**Multiple selections allowed**).
a. Walk to the office when commuting
b. Go to the gym to workout
c. Use stairs instead of elevators
d. Participate in exercise programs at work
e. Take a walk in the company
f. Other:

9. What kind of wearable activity tracker did you use in the past? (**Multiple selections allowed**).
a. Fitbit
b. Samsung Gear Fit
c. Xiaomi Mi Band
d. Jawbone Up
e. Garmin VivoFit
f. Nike FuelBand
g. Shine
h. Zikto Walk
i. Other:

10. Which biometric data did you measure with the device? Which data did you take an interest? (**Multiple selections allowed**)
a. Steps
b. Heart Rate
c. Distance
d. Calories
e. Sleep
f. Other:

11. Please rate the level of stress that you receive at work in the scale of "1 - do not take stress at all" to "5 - get stressed the most"?
a. 1
b. 2
c. 3
d. 4
e. 5

12. How long have you used a wearable activity tracker?
a. Less than 1 week
b. Less than 1 month
c. Less than 3 months
d. Less than 6 months
e. Less than 1 year
f. Less than 2 years
g. More than 2 years

13. When you first started using the device, how did you perceive your fitness status and exercise?
a. I am not physically active, and I don't plan on doing any physical activity in the near future
b. I am not active at the moment, but I am thinking about being more active
c. I am preparing to do more activity and intend to start in the next month
d. I have been physically active for less than 6 months
e. I have been physically active for more than 6 months

14. Please indicate below when you started using the device that you are selling at the second-hand market (i.e., May 2016).

15. If you have stopped using the device that you are selling at second-hand marketplace, please indicate below when you stopped using it (i.e., March 2017).

16. How did you first get the device you used?
a. Made purchase personally
b. Received as a gift
c. Won at an event
d. Received from the company (via an exercise program)
e. Other:

17. How often did you wear (use) the device you used?
a. Everyday
b. Once a week
c. Once a Month
d. Once or Twice per year
e. Other:

18. Why did you choose the device you used? (**Multiple selections allowed**)
a. Other people were using it a lot
b. The price was reasonable
c. Its design was attractive
d. Its features seemed helpful
e. It was recommended by friends / family
f. Received as a gift
g. Other:

19. What motivated you to start using a healthcare wearable device? (**Multiple selections allowed**)
a. To increase the amount of physical exercise (to be healthy)
b. I was curious about the healthcare wearable devices
c. To get to know myself better with the information provided by the device
d. I wanted to try it on because it has a nice design
e. Other:

20. Why are you no longer using the device? (**Multiple selections allowed**)
a. It was uncomfortable to use
b. The device seemed not so helpful for exercise
c. I kept forgetting to wear it everyday
d. Its design is not appealing
e. The information provided by the device is not useful
f. The measurement for exercising (physical activity) is not accurate
g. It has too many features
h. Other:

21. Similarly, if you are now selling this device at a second-hand market, what is the reason? (**Multiple selections allowed**)
a. Measuring how much exercise (physical activity) I do is no longer my concern
b. I developed a health problem
c. I already achieved my goal by using the device (i.e., successfully lost weight)
d. Its functions fell short of my expectations
e. I have a similar device
f. Its size does not fit
g. Due to financial reasons
h. Made a wrong purchase or received a wrong gift
i. It is too complicated to use
j. To buy a better device
k. Due to changes in daily life (i.e., changed job)
l. Other:

22. Which of the features did you mainly use when using the device? (**Multiple selections allowed**)
a. Tracking physical activity
b. Viewing the data provided by device via a website or mobile
c. Competing with friends who are registered on the device
d. Sharing health data on SNS
e. Setting own goals
f. As a Clock or alarm

23. Was there any change in your life once you stopped using the device? Please indicate below in detail. (i.e., I keep looking at my wrist thinking that I am still wearing it)

24. Did you have any emotional changes once you stopped using the device? If so, what kind of emotional change would it be?

a. No change
b. Frustration
c. Guilt
d. Freedom

25. Which of the features do you consider to be the most important for the wearable activity tracker?

a. Design
b. Convenience
c. Appropriate Feedback
d. Competing with your friends on social networks
e. Setting a goal

26. Do you think you would use wearable activity tracker again in the future?

a. Yes
b. No

27. Please indicate what you liked or disliked about wearable devices. Also, if you have a wearable device that you are currently using in addition to the one you are selling at marketplace, please write below.

**Thank you for your reply!**

## APPENDIX E. INTERVIEW GUIDE

**Survey on the disuse of wearable activity tracker in everyday life of office workers**

1. Purpose of the interview (An introductory remark to participants prior to the interview)

This research is a study on the information behavior and perception towards the use of healthcare wearable device held by its users among office workers in Korea. The interviews will be conducted in the same way for all interviewees, and the data will be collected through an integration of semi-structured interviewing and data analysis methods.

- There is no correct answer to the interview question.
- Interview will last around 45 – 60 minutes.
- The interview will be suspended at any time if the interviewee feels uncomfortable or no longer wants to participate in the interview.
- This research plan will primarily be used for academic purposes and will be provided only as a reference for policy and/or institutional arrangements.

2. Common questions about wearable devices

1) What kind of model of Fitbit are you using now?
2) Is there a wearable device that you used before Fitbit?
3) How long have you used the wearable device (Fitbit)?
4) How often did you wear (use) the device you used?
5) Have you ever recorded your activity before using a wearable device?
a. i.e. via Mobile apps, diary, etc.
6) Are you using other devices or apps besides Fitbit (sleeping or food journaling)?
7) How did you first get the device you used?
8) Why did you choose the device you used?
9) How did you first hear about Fitbit?

**Physical Activity**
10) How often do you exercise? Which exercise do you mainly do?
11) Do you often have time to exercise at work?
12) What do you usually do during a break at work? (i.e. Internet, walking, drinking coffee, smoking)
13) Which transportation do you usually use when commuting to your workplace? Your car? Bus? Subway?

3. The motive for using wearable devices

14) What motivated you to use this device? Did you have any specific motivation?
15) What do you like about this device?
    a. Which service (or feature) provided by the device is helpful?
    b. What makes this device inconvenient to use?

16) Why do you continue to use the device? (i.e. Feels like something is missing if not wearing it)
17) What are the impediments for the consistent use of the device? (i.e. Does not go with my fashion)
18) Which of the features did you mainly use when using the device?

4. The usability of wearable device

19) How does it fit on your body?
    a. Does wearing the device have any influence on your behavior?
    b. How did people react when you wore it on your wrist?
20) Are there any inconveniences to wear or carry it around?
a. When and where do you wear your device and take it off?
b. When do you charge the battery?

5. The use of wearable devices in the information aspect (information representation)

21) What kind (or form) of information is provided by the device?
    a. Do you find the device's supportive messages or emoticons helpful?
22) How useful is the information generated by the device?
    a. Do you think the information is accurate?
    b. How much do you trust the data?
23) Is there any change in your activity from getting information (biometric data)?
24) Do you use Fitbit applications on mobile?
    a. How often do you check activity on the web or mobile?
25) Do you use the website to check your activity?
26) Is there any difference between the information displayed on the mobile, website, and device?
27) Are you satisfied with the presentation of information on your activity? Any suggestion for improvement?

6. Behavioral change

28) Are there any changes in behavior since you use the device?
    a. Is there any difference in your behavior between before and after using the device?
    b. If yes, please provide a specific example. (i.e. motivated to become more active or to be able to quantify the activity from the provided information)
29) Which functions of the device have the greatest impact on your behavioral change?
    a. Goal setting, feedback service, challenge and competition program with friends / acquaintances, Social aspect
30) Have you been able to record your physical activity better by using the device?
    a. Which information do you think is the most important among steps, calorie consumption, moving distance, and moving time?
    b. Similar to the questionnaire but which biometric data did you mainly measure through the device? Which data did you focus on? Why were you particularly interested in that information?

7. Social aspects (social communication)

31) Do you use social media like Twitter or Facebook?
32) Are you using the service that allows you to check the activity data of your friends / family/ acquaintances? If yes, do you often check their activity? Or have you sent a cheer up message?
33) Have you ever shared your data from Fitbit on SNS? If so, how?
34) What do you think about sharing this data with the doctors in the future?
35) Do social communications induced by using this device affect your behavior?
36) Did you join the Fitbit social community? Do you visit the website often?

8. Data Aspects

37) Do you receive your personal data in an Excel file or do you store the data separately on your computer for later use?
38) What do you think of your data? Are you generally satisfied? Or does it fail to meet your expectations?
39) Do you think this data will be meaningful to you in the future? Or do you think it's just one-time use?
40) Do you track your heart rate using the device? If so, when do you find it useful?

9. Open-end question
Please inform us of the improvements that should be made or the things you did not like when using the wearable device. And please tell us what you usually think about tracking data on these wearable devices (i.e. I think it is helpful, and the data will be meaningful in the future)

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