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# Kommunikationsmuster durch Smartphone-Nutzung

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# Communication Patterns on Smartphone Usage

DIPLOMA THESIS

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by

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# Declaration of Authorship

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Lastly, we want to thank each other for collaborating, working hard, and being committed. Our teamwork and support were crucial in achieving our objectives and overcoming the obstacles we encountered during the process.

# Kurzfassung

In den letzten 10 Jahren sind Smartphones aus dem täglichen Leben nicht mehr wegzudenken. Mit zunehmender Nutzung sind Kommunikation-Apps zu den am häufigsten verwendeten Apps geworden. Die Menschen verlassen sich täglich auf sie, um mit Familie und Freundeskreis zu kommunizieren, aber auch um berufliche Aufgaben zu erledigen. Die allgegenwärtige Präsenz von Smartphones hat die Forschung dazu veranlasst, sie als gewohnheitsbildende Geräte einzustufen, da sie so konzipiert sind, bei jeder Nutzung Belohnungen zu bieten, was die Nutzer:innen dazu veranlasst, sie ständig zu verwenden. Die Dauer der Nutzung, die Häufigkeit der Überprüfung, der Wechsel der App und das App-Wiederholungsverhalten sind die wiederkehrenden Muster, die untersucht wurden, um die zugrunde liegenden Faktoren zu identifizieren, die eine gewohnheitsmäßige Nutzung von Smartphones begünstigen.

Um die zugrundeliegenden Probleme der zunehmenden Smartphone-Nutzung anzugehen, konzentriert sich diese Arbeit auf den Kontext, in dem Kommunikation-Apps genutzt werden, wobei klar zwischen Freizeit und Arbeitszeit unterschieden wird, um besser zu verstehen, ob eine Änderung des Kontexts das Nutzerverhalten in Bezug auf Dauer und Häufigkeit der Nutzung beeinflusst. Die Forschungsfragen lauten daher: "Wie verhalten sich die Nutzer:innen von Kommunikation-Apps hinsichtlich Dauer und Häufigkeit in der Freizeit?" und "Wie verhalten sich die Nutzer:innen von Kommunikation-Apps hinsichtlich Dauer und Häufigkeit in der Arbeitszeit?". Zur Beantwortung der Forschungsfragen wurden die zuvor erhobenen Protokolldaten von 75 Teilnehmer:innen ausgewertet. Die Ergebnisse wurden durch einen quantitativen Forschungsansatz mit Hypothesentest und Explorativer Analyse gewonnen. Die Ergebnisse deuten darauf hin, dass eine Veränderung des Kontexts das Nutzungsverhalten von Kommunikation-Apps in Bezug auf Häufigkeit und Dauer beeinflusst. Nutzer:innen in der Freizeit verbringen mehr Zeit mit Kommunikation-Apps und nutzen diese häufiger als Nutzer:innen in der Arbeitszeit. Darüber hinaus wurden Cyberslacking während der Arbeitszeit und arbeitsbezogene Aktivitäten in der Freizeit festgestellt. Was über den Kontext hinauszugehen scheint, ist die Auswahl der Kommunikation-Apps. WhatsApp und Facebook sind die beiden meistgenutzten Kommunikation-Apps in beiden Bereichen. Dies deutet darauf hin, dass das Bedürfnis nach sozialen Interaktionen für die Gewohnheitsbildung wichtiger ist als der Kontext.

# Abstract

Over the past decade, smartphones have become an essential part of people's lives. Along with their increase in usage, communication apps have become the most frequently accessed. People rely on them daily to communicate with their family, friends, and colleagues, but also to perform work-related tasks or stay up to date with the latest news around the world. The ubiquitous presence of smartphones led research to categorising them as habit-forming devices, due to their purposeful design to offer rewards with every engagement, which lures users to constantly check on them. Duration of use, frequency of checking, app-switching and revisitation behaviour are the recurrent patterns investigated to find the underlying factors that promote a habitual use of smartphones.

To tackle the underlying issues that come with increased smartphone usage, this work focuses on the context in which communication apps are used by clearly separating between the leisure and work domains to better understand if changing the context has an effect on users' behaviour regarding the duration and frequency of use. Therefore, the research questions are: "How do users behave with smartphone communication apps in terms of duration and frequency when at leisure?" and "How do users behave with smartphone communication apps in terms of duration and frequency when at work?". To answer the research questions, previously collected log data of 75 participants has been analysed. The results were obtained by following a quantitative research approach, including hypotheses testing and exploratory analysis.

The results indicate that changing the context influences users' behaviour patterns of communication apps usage in terms of frequency and duration. Users at leisure spend more time and check communication apps more frequently than users at work. Furthermore, cyberslacking behaviour during work-time and work-related activities during leisure-time were identified. What seems to go beyond the context is the choice in apps. WhatsApp and Facebook are the top two most used apps across both domains, implying that the need for social connection overrules the context regarding habit formation.

# Distinction of Joint Work

The current work represents a joint effort between Bruna Kapaj and Iulia-Cristina Hatiegan. The research was divided into two main domains: leisure and work.

Regarding the theoretical background, Bruna focused on researching the leisure domain, while Iulia examined the work domain. However, there were specific topics within the theoretical part where they collaborated in reviewing the literature together such as, Boundary Theory and Habit Formation Theory.

As for the analysis part, the data cleaning and preparation as well as the decision making on the best approach for analysing the data were conducted together. Nonetheless, the analysis of each domain was carried out independently; however, we maintained regular discussions to share our findings and interpretations.

Throughout the entire research process, we collaborated closely, drawing on each other's strengths and knowledge to create a comprehensive and thorough study.

# Contents

# CHAPTER 1

# Introduction

Over the past decade, the use of smartphones has skyrocketed since they have become a gateway to the internet and social media, improved e-commerce, and have contributed to economic growth (Sela et al., 2022). With the increase of smartphone usage, communication apps have become the most frequently accessed apps among users (Jeong et al., 2020).

WhatsApp is reported to have more than 2 billion monthly active users globally, who are sending over 100 billion messages each day, according to a December 2020 tweet from Will Cathcart, the Head of WhatsApp (Dean, 2022). Similarly, over 150 million video calls are made on Facebook Messenger every day and more than 200 million videos are sent (Micheva, 2020). These apps have become deeply ingrained in modern society to the point that limiting or prohibiting their use is seen as a punishment by both adults and teens (Sela et al., 2022).

These numbers demonstrate the tremendous reach that communication apps have gained over the years, which in turn has led to an overall increased usage of these apps. As a result, people started feeling technostress in both private and professional life (Khan & Mahapatra, 2017). Furthermore, cyberslacking behaviour (Jeong et al., 2020) is more and more common at the workplace, creating a reason for concern for organisations, and employees' well-being. One important reason behind this is the blurring of boundaries between leisure and work domains, allowing for work to intrude private life and vice-versa (Williams, 2019), thus violating set boundaries (Ashforth et al., 2000).

Previous research has already indicated that smartphones along with communication apps are habit-forming due to the notification feature they all offer (Renfree et al., 2016). By providing regular updates to the users, they are lured to constantly check their smartphones, and develop a checking habit (Oulasvirta et al., 2012). If the feeling is rewarding for the users, then they feel encouraged to check it regularly, hence creating a linkage between the cue and behaviour and developing a habit (Wood et al., 2014).

Out of these reasons, further research has been conducted to identify what types of habit-forming patterns do users cultivate by engaging with their smartphones. The recurring patterns are: usage patterns based on duration of use (Bohmer et al., 2011; Deng et al., 2019; Montag, Błaszkiewicz, Lachmann, et al., 2015), usage patterns based on smartphone checking (Monge Roffarello & De Russis, 2022; Oulasvirta et al., 2012; Yan et al., 2012), usage patterns based on app-switching behaviour (Jeong et al., 2020; Monge Roffarello & De Russis, 2022), and usage patterns based on revisitation behaviour (Jones et al., 2015; Tian et al., 2020).

However, the main shortcoming identified, is the lack of research that focuses on the habit-forming nature of communication apps usage alone by clearly separating the domain in which these occur, although an association between the context and environment has been determined (Y.-K. Lee et al., 2014; Walker et al., 2015). Therefore, this work will answer the following research questions: **how do users behave with smartphone communication apps in terms of duration and frequency when *at leisure*?** and **how do users behave with smartphone communication apps in terms of duration and frequency when *at work*?**. By doing so, it will try to make the differences and similarities evident regarding communication apps usage between the leisure and work domain, hence drawing conclusions on how the context affects users' behaviour. Lastly, it will address any potentially identified behaviours that highlight the blurring boundaries between private and professional life (Derks & Bakker, 2014), with the intention of laying a foundation for future research that will try to tackle the underlying factors behind it.

The remainder of this work is structured as follows: Chapter 2 presents the theoretical background in detail, starting with the evolution of smartphone communication behaviour, and technostress. Then, the blurred boundaries between leisure and work build the foundation for discussing each domain individually regarding smartphones and communication apps. Next, the habit-forming nature of smartphones is addressed. Lastly, the chapter concludes with the presentation of the recurring habit-forming patterns developed by users from smartphone usage overall, before delving into the context of each domain. Chapter 3 addresses the methods of this work, detailing the collection, description, and preparation of the data. It concludes with the analysis procedures conducted to answer the research questions and introduces the obtained results. These are then discussed along with the literature findings in Chapter 4 where also the limitations and implications are addressed. Finally, the work concludes with an overall conclusion in Chapter 5.

CHAPTER 2

# Theoretical Background

## 2.1 Smartphone Communication Behaviour

As smartphones have become an essential tool in modern life, research has shown that they are heavily utilised in a variety of domains, including both work and leisure domains (Jeong et al., 2020). Due to the widespread use of smartphones, it is now possible for people to stay connected at all times, whether they are at home, at work, or on the go. This continuous connection has revolutionised the way people communicate as well as access information, allowing them to easily connect with friends and family, access the internet, and perform a variety of tasks, from checking their emails to managing their finances. The impact of smartphones on society has been profound, changing not only the way people interact with technology but also the way they communicate with one another (Phua et al., 2017).

Smartphones nowadays offer a range of features, options and apps, but the communication apps remain the most used type of smartphone apps (Jeong et al., 2020) as they account for 49% of the overall time spent on a smartphone and 35% against all apps (H. Li et al., 2015). These platforms have become an integral part of society, with over four billion global active users who spend an estimated minimum of two and a half hours per day on these apps for various purposes (Kemp, 2023). The availability of diverse communication channels makes smartphones a popular tool for handling high volumes of communication. An interesting discovery is that communication apps are being used hourly during a day and making up for over 50% of overall smartphone usage, emphasising the need of feeling connected (Bohmer et al., 2011).

The constant need for connection and communication with others has become a defining characteristic of modern society, and this need is a major factor driving the widespread use of communication apps. Many people feel a desire to be constantly connected to their friends, family, and social networks, and they use communication apps to fulfil this need. Research has established that there are positive aspects of their use besides the connectivity they offer, such as promotion of the innovative ideas (Bhimani et al., 2019) and work-related performance (Bodhi et al., 2022).

While communication apps have clearly made it easier for individuals to stay connected, there is a growing concern about the negative consequences of overuse. According to research, extended usage of these apps can have a negative influence on users' mental health and productivity (Thomée et al., 2011), as well as a negative impact on users' emotional states, generating stress and worry (Y.-K. Lee et al., 2014). Additionally, the excessive use of communication apps can interfere with daily tasks and reduce overall productivity (Tarafdar et al., 2010). This is due to the constant stream of messages, which makes it easy to get side-tracked and lose focus, leading to a decrease in efficiency and quality of daily tasks. Moreover, the use of these apps has also been linked to reduced sleep quality, as the constant need to check for updates can disrupt one's sleep patterns and even lead to sleep deprivation (Yogesh et al., 2014).

Moreover, a noteworthy phenomenon when it comes to communication apps is the Fear of Missing Out, also known as FOMO. This unique term was coined by Patrick J. McGinnis in a 2004 op-ed in The Harbus, the magazine of Harvard Business School (McGinnis, 2004). It is used to describe a phenomenon observed on social networking sites which includes the perception of missing out on social interactions, social information, or other experiences that others may be having. It also involves the necessity felt by people to maintain these social interactions, which can also manifest in other ways, such as the fear of being left out of social groups. This may cause someone to feel under pressure to reply to text messages, notifications, or social media updates right away, even at the expense of their own well-being (Thomée et al., 2010). Over the course of time, this behaviour can lead to a sense of necessity to maintain these social interactions, making the user experience feelings of anxiety and stress (Hattingh et al., 2022).

What is also worth noting is the fact that the overuse of communication apps is associated to time distortion. This happens when people use these apps for longer periods of time than they intend or perceive. As a result, this can have a negative impact on people's well-being, such as increased stress levels and decreased productivity. Moreover, the perceived distortion of time can also cause people to neglect other important aspects of their lives such as personal relationships, physical exercise, and mental health activities, leading to an overall decrease in their health (Lin et al., 2015). Talking about these two types of smartphones use mode, one where the user is aware of the time he spends (aware mode) on his smartphone and one where the user perceives another reality (unaware mode), it is noteworthy to mention that research has demonstrated how excessive smartphone usage without awareness is much more harmful to the quality of life compared to smartphone usage with awareness.Therefore, it is not just about how much time users spend on their smartphones, but also the mode in which they use them that affects their quality of life. It is important to limit multitasking or performing other tasks while using smartphones in order to minimize the harmful effects of excessive smartphone use on the overall well-being (Sela et al., 2022).

Another intriguing aspect of communication apps and the behaviours associated with them is that they are connected to one another. A previous study looked at the relationship between engagement with one social media app and the subsequent use of other social media platforms. The researchers found that participants who engaged with one social media app were more likely to continue using their smartphones to access other social media apps, resulting in prolonged usage beyond their intended timeframe. This phenomenon of inter-connectivity indicates that communication apps usage is not limited to one app but rather a complex web of interconnected platforms that can increase compulsive use and the risk of addiction (Marciano & Camerini, 2022). This phenomenon is evident in the monthly usage statistics of popular social media apps such as Facebook, WhatsApp, and Instagram, which collectively consume a significant portion of users' time. For instance, users spend an average of 20 hours per month on Facebook, 17 hours per month on WhatsApp, and 12 hours per month on Instagram, highlighting how just these three communication apps can occupy a substantial part of a user's daily activities (Kemp, 2023).

To go deeper into smartphone communication behaviour patterns, some studies have gone even further and shown that this habitual behaviour could potentially lead to uncontrollable usage and smartphone addiction (Y.-K. Lee et al., 2014; Oulasvirta et al., 2012). This addiction has been proven to lead to even lower productivity and even more stress for the users in their personal life. It is worth mentioning that smartphone addiction has been found to be more strongly associated with leisure time spent on apps rather than work-related communication. This suggests that smartphone addiction may have a greater negative impact on daily activities outside of work (Duke & Montag, 2017) accompanied as well with stress and anxiety (Y.-K. Lee et al., 2014). Furthermore, in a prior study, more than half of the participants were aware of their smartphone addiction and this finding matched and was consistent between what they self-reported and the log information from the data collected. However, to be noted is the fact that they did not consider their addiction as problematic (Deng et al., 2019).

While investigating whether smartphone usage can be considered addictive behaviour or not, a previous study has mainly researched this topic with the goal of tackling the problem and identifying solutions to eliminate addiction. M. Lee et al. (2018) looked at college students' smartphone addiction levels based on the amount of time they spend on their smartphones. The results showed that the main apps used by them are social networking, music, communication apps and search engines. Out of all the students who participated, almost 5% were exposed to a high-risk and 13% had a potential risk of smartphone addiction. Furthermore, A. R. Lee et al. (2016) identified a high usage of communication rather than entertainment apps, mentioning that even when there is no need, people want to be perpetually connected to others. This can be explained by the loneliness people experience in the busy society they live in and finding an escape to get a sense of belonging to a community or friends in the online world (Salehan & Negahban, 2013).

In conclusion, when considering communication apps, it is evident that social media has become the preferred method of communication both at the workplace and in the home domains. As such, understanding the impact of social media and communication apps on the user himself as well as on the formation of behaviours in these domains is a significant key of the existing research and sets up the foundation for further exploration in this work.

### 2.1.1 Technostress

The aforementioned high usage of communication apps can on one hand invoke positive aspects such as access to information, entertainment, productivity as well as facilitating fast communication with family and friends all around the world (Salehan & Negahban, 2013). On the other hand, the excessive use of these apps has been shown to contribute to social isolation and loneliness (Thomée et al., 2010). Not only that, but it has also been accounted for being a source of negative feelings and stress (Y.-K. Lee et al., 2014). In this case, the latter is often referred to as technostress, a term coined by clinical psychologist Craig Brod in the 1980s who defined it as "a modern disease of adaptation caused by an inability to cope with new computer technologies in a healthy manner" (Brod, 1984). It is often used to describe a form of occupational stress that is associated with information and communication technologies and it is perceived both in the working and personal domains (Fischer & Riedl, 2015; Khan & Mahapatra, 2017; Y.-K. Lee et al., 2014).

It is therefore essential that, to better understand the phenomenon of technostress one needs to look into both the underlying causes of these stressors as well as the effects they have on users in the context of social media and communication apps.

Examining the several reasons behind technostress, the overload of information and communication that users receive also known as Techno-Overload is one of the main factors that contribute to this phenomenon (Tarafdar et al., 2010). In a previous study, users noticed that because of the constant flow of chat or emails, it was difficult to select essential messages over less important ones. Participants frequently struggled to reply to all messages as quickly as they felt expected to, resulting in feelings of guilt, frustration, and stress when they were unable to keep up with the speed of communication. Other consequences included mental overload, neglect of other activities and personal needs, time pressure and social isolation (Thomée et al., 2010). Research has also shown that there is a positive association between information overload and FOMO (Hattingh et al., 2022). When it comes to social media, information overload can contribute to FOMO because users find it difficult to keep up with the never-ending flow of information, which puts even more pressure on them to be continuously connected. As a result of the overwhelming quantity of information and triggers, the individual's mental and emotional resources can become exhausted, leading to feelings of nervousness, irritation and another interesting phenomenon called social media fatigue (Hattingh et al., 2022; A. R. Lee et al., 2016).

Additionally, another stressor is the pressure of being available and reachable at all times, additionally referred to as Techno-Invasion (Tarafdar et al., 2010). This expectation of constant availability can be a significant source of stress, as people may feel obligated to respond to messages and notifications immediately when they receive them, no matter what time of day it is - even at night time (Thomée et al., 2011). The expectation of availability is influenced by multiple domains, including work and study, the social network, broader society and the individual participants themselves. Receiving a large amount of phone calls and text messages in these domains often results in anxiety or guilt, as people are expected to give reasons for being unable to reply to these types of communications (Thomée et al., 2010). One interesting finding has been that users also differentiate between the type of communication that they feel the need to respond to immediately. In a previous study, nearly all participants reported that they consider text messages to be more urgent and require immediate responses compared to most emails. When it comes to responding to emails, the majority of people take 2-3 days on average (Agarwal et al., 2022).

As a consequence, besides the stress, many young people experience the emotions of guilt and the feeling of never being free because they are unable to respond to all the calls and text messages as a result of the constant accessibility provided by smartphones (Thomée et al., 2010). Additionally, continuously checking for new messages and notifications has been shown to be distressing and could even lead to distraction from other tasks - whether those tasks are related to the work domain or not. Another consequence is the effect that this stress factor has on the sleep patterns of the users, which in turn leads to significant impacts on health and well-being. Participants of studies have reported that a high volume of phone calls and messages can make it challenging to relax, resulting in insufficient sleep or poor sleep quality. Notably, the most significant factor linking smartphone use to sleep disturbances was being woken up by phone calls or messages during the night, which compelled individuals to check and respond to them, further affecting their sleep (Thomée et al., 2011).

Major consequences of technostress can also be observed in the work domain. For example, in the event of users feeling the need to respond to messages, calls or emails outside of normal working hours, as part of Techno-Invasion. One of the main factors contributing to this is the around the clock availability of technology, which simplifies the ability of employees to remain connected to the workplace even when they are at home during their leisure-time (Perlow, 2012). It was identified that the amount of time needed to reply to emails outside of working hours has a positive correlation with increased levels of anger. Additionally, employees who maintain a constant connection with their work through the use of smartphones face significant challenges in achieving psychological detachment from work. These employees experience work-home interference, which hinders their ability to effectively recover from work-related stress and strain. Put simply, the habitual use of smartphones for work purposes negatively affects employees' recovery process (Derks et al., 2015).

This behaviour not only can be stressful for the employee himself but also for the people in their lives, especially those at home, as research has shown that techno-stressors have a negative impact on the work-life balance (Ma et al., 2021). The pressure to be available for work-related communication at all times can contribute to what is called the "blurred boundaries between work and leisure", making it difficult for employees to switch off and relax outside of working hours (Fonner & Roloff, 2012) as well as the fact that employees find it difficult to separate work and private life from one another (Thomée et al., 2010).

In keeping with the consequences of technostress on the work domain, it has been determined that it also has negative effects on the employees' job performance in multiple ways. One significant impact is a decrease in productivity, as employees may become distracted by their smartphones or overwhelmed by the constant flow of communication. This was shown to be also related to multitasking, which occurs when employees use their smartphones to participate simultaneously in several activities, and such behaviour divides their attention and undermines the process of learning (Madden, 2017). What is more, the level of stress experienced was positively linked to the degree of multitasking (Mark et al., 2014). Furthermore, it can result in slower completion of tasks, missed deadlines, and an overall reduction in their tasks output (Tarafdar et al., 2010). This may lead to employees feeling frustrated and dissatisfied with the technology being used, which can ultimately result in lower end-user satisfaction (Duke & Montag, 2017; Tarafdar et al., 2010). Lastly, Khan and Mahapatra (2017) have also indicated that technostress has a detrimental impact on organisational performance, as it amplifies role stress and diminishes job satisfaction, productivity, and performance of the workforce. Therefore, the repercussions of technostress cannot be ignored by organisations as it negatively influences employees' quality of work.

In conclusion, using smartphones and communications apps frequently can lead to stress and other challenges for users. The pressure to maintain social connections, information overload, the expectation of constant availability, and the pressure to respond to work-related communication outside of working hours are some of the technostress creators in today's society. These can cause nervousness (Hattingh et al., 2022; Tarafdar et al., 2010; Thomée et al., 2010), guilt, frustration, mental overload, sleep patterns disorders, social isolation, and social media fatigue (Hattingh et al., 2022; A. R. Lee et al., 2016; Thomée et al., 2010). Such factors can also have a negative effect on work performance, end-user satisfaction, and general health and well-being by increasing technostress and decreasing productivity (Duke & Montag, 2017; Ma et al., 2021; Tarafdar et al., 2010).

Understanding the connection between technostress and typical smartphone communication behaviour is important, since they are frequently associated with social media use. Social media has become an unavoidable part of daily life, and its usage can have a habit-forming effect, making it difficult to break free from the habits and behaviours associated with it. Therefore, identifying the stressors connected with smartphone communication apps is, in fact, only one aspect of the issue. It is also noteworthy to understand the behaviour patterns that users develop while using these apps and how these patterns may contribute to the formation of difficult-to-break behaviours.

## 2.2 Blurred Boundaries between Leisure and Work Domains

People spend at least one part of their day working, and before technology became omnipresent, once they were leaving the work premises there was less possibility to remain fully engaged in work. Nowadays, technology is carried in the form of smartphones, tablets, and notebooks everywhere one goes, be it at home or on the road (Davis, 2002). The emergence of smartphones and different digital tools has resulted in a significant influence on the available opportunities for work in relation to the manner and timing in which tasks are carried out.

Today's employees seek the freedom to choose and regulate their work schedule and techniques (Kane, 2015). This can be already noticed by the increase in non-traditional working hours (Härmä, 2006). Therefore, organisations which want to be at the forefront, rather than opting for a fully remote or in-office work model, have already started adopting a hybrid work model, where employees divide their work time between remote and office-based work (Yang, 2021). This enables people to stay connected around the clock without having a clear separation of work- and leisure-time, thus creating blurred boundaries between these domains (Williams, 2019).

According to boundary theory, boundaries have two key related characteristics: flexibility and permeability. Flexibility refers to an individual's ability to move between different domains and adjust to the demands of each domain, whereas permeability refers to the extent to which an individual's boundaries can be crossed or intruded upon by demands from other domains. This can lead to challenges in maintaining a work-life balance, especially in cases where work demands intrude upon personal time or vice versa (Nippert-Eng, 1996).

While work-family policies such as flextime, telecommuting, and family-friendly benefits are often implemented by organisations to help employees manage their work and family domains, it is important to note that these policies are not one-size-fits-all solutions. While they may work well for some employees, they may not be as effective for others (Kossek et al., 2011). This is because individuals vary in the extent to which they integrate or segment their various roles across domains, and their boundary management strategies may not align with the policies that are offered by their organisations (Olson-Buchanan & Boswell, 2006).

Boundaries, whether physical, temporal, or behavioural are crucial for structuring and separating the various roles an individual maintains in different domains, such as work and family (Olson-Buchanan & Boswell, 2006). Therefore, following a boundary management strategy which refers to the set of principles that an individual uses to manage and separate their different roles and responsibilities between home and work can be beneficial. It can help to establish clear boundaries between personal and professional life, enabling individuals to meet the demands and expectations of both domains effectively (Kossek & Ozeki, 1999).

Nevertheless, for some people, the boundaries between work and personal life may be more blurred, while others may maintain a clearer separation. In most jobs, individuals have some control over the extent to which their personal and professional boundaries are permeable or flexible. In other words, employees have some degree of autonomy or discretion in determining how much they blend their personal and professional lives together, and how much they decide to keep them separate. For example, an employee might decide to check work emails outside of traditional working hours, or they might choose to keep work-related tasks strictly within working hours (Olson-Buchanan & Boswell, 2006).

However, with the advent of smartphones that offer ease of use and ability to keep them around all the time, organisations have decided to not only adopt them but apply them in a wide-ranging of tasks, making them indispensable (Porter & Kakabadse, 2006). As a result, employees who strive to keep work separated from private life face a challenge in doing so. Contrarily, modern smartphones users who appreciate the ease of communicating with members of work and family, see smartphones as a support to help them meet goals both at work and at home. With the provided ability to stay connected around the clock (Tarafdar et al., 2010), they can better manage their responsibilities and maintain a sense of control over their work and family domains (Hunter et al., 2019). Consequently, it has been shown that not only technology but also employees themselves contribute to the blurred boundaries between work and leisure through repeatedly checking on work matters during leisure-time, making it very challenging to reverse this trend (Colbert et al., 2016).

In addition to the challenges posed by modern technology and employees in blurring the boundaries between work and family domains, there is also the issue of boundary violations. Boundary theory posits that work-family conflict arises as a result of the accumulation of daily events that breach the boundaries between work and family domains. These events are called boundary violations, and they can take many forms. For instance, a call from a family member during work hours can violate work boundaries while an off-hours business meeting can violate family boundaries (Ashforth et al., 2000).

Organisations' culture may support family boundaries violation. They are rising their demands with respect to employee's availability (Porter & Kakabadse, 2006) constraining them to reply promptly to any work requests even outside of work (Davis, 2002). This is due to the emergence of technologies that facilitate a higher work portability and around the clock connectivity with the workplace and work colleagues (Porter & Kakabadse, 2006).

At the same time, the technological advancements in data generation and transportation have resulted in a constant sense of urgency especially for employees. This is due to the ease at which the information can be generated and made available everywhere, as well as the consequent expectation that employees should use it promptly and may even have a responsibility to do so (Davis, 2002). Additionally, it can also be perceived as an endorsement from the organisation, thus leading to an increased likelihood of their use for supplementary work at home (Fenner & Renn, 2004) making employees believe that they are expected to access work beyond regular working hours (Derks et al., 2015).

In particular, if this influence comes from a direct manager at work, it would make it even more difficult to resist as the employer could think it would help him advance more easily within the organisation. As a result, a corporate culture that recognizes and rewards employees who demonstrate a strong work ethic was adopted. Also, employees who present a willingness to devote extended periods of time to their job and maintain constant connectivity to their workplace were favoured (Kakabadse, Nada K and Kouzmin, Alexander and Kakabadse, Andrew K, 2017). In conclusion, the expectations of today's organisations can act as family boundary violations, due to encouraging employees to give up their private time for work, which can have a direct relationship with work-family conflict.

If the boundaries are stretched over the limit of an individual, then their well-being may also get affected. On one hand, when work boundaries are violated, it could cross over into the individual's personal life and create conflicts between work and family responsibilities, thus impacting it negatively. Similarly, boundary violations at work could lead even to dissatisfaction with the job itself. On the other hand, when boundaries are crossed at home, it can result in conflict between work-family. Additionally, when boundaries are violated at home, it can indirectly lead to lower satisfaction with investment in family, and this is partly because of the obstruction of family goals (Hunter et al., 2019). As a result, boundary violations, such as using the smartphones for work-related activities during leisure-time or being required to be "on call" during non-work hours were shown to lead to work-related exhaustion, and negative emotional states such as anger or irritation. Additionally, they can have an adverse effect on the individual's mood the following day (Butts et al., 2015; Dettmers et al., 2016; Wayne et al., 2017).

Interestingly, apart from negative cognitive emotional reaction, it was found that boundary violations can evoke also positive ones. This was true both for boundary violations at work and at home. For boundary violations at work, a positive influence was partly explained by the fact that the violations helped with family goals, tightening the relationships at home. For boundary violations at home, the positive relationship was fully explained by the fact that they helped with work goals, leading employees to devote more time and effort to work (Hunter et al., 2019).

In general, the well-being of employees appears to be significantly influenced by psychological factors associated with their perceptions of job control and boundary management. It was revealed that a noteworthy correlation between a stronger sense of psychological job control and reduced turnover intentions, as well as a decrease in both family-to-work conflict and symptoms of depression. Conversely, individuals who employed integration-based boundary management strategies tended to experience higher levels of conflict between their work and family life. These findings highlight the complex nature of flexibility and emphasise the pivotal role of psychological experiences in determining an individual's overall well-being. To conclude, it was identified that two primary factors consistently predicted higher levels of well-being: (1) a greater degree of job control over aspects such as work location, timing, and methods; and (2) a boundary management approach that prioritises maintaining a clear separation between work and family domains(Kossek et al., 2006).

All considered, the advancements in technology have extended temporal and spatial boundaries at work (Davis, 2002), encouraging employees to perform tasks outside of the regular working hours which has led to increased workload and labour intensity (Porter & Kakabadse, 2006). This in turn, resulted in a high pressure for employees to work continuously (O'Neill et al., 2014) and caused the loss of work-life balance by blurring the boundaries between work and leisure domains, creating significant concern (Adisa et al., 2017). Not only that but it also violates set boundaries, thus having an impact on work and family. Therefore, employing a boundary management strategy is essential nowadays (Olson-Buchanan & Boswell, 2006). Moreover, the introduction of work on smartphones made it very easy to transfer it into employees' private lives, making work-related stress more prominent in the personal space, affecting well-being. Therefore, employees should aim at maintaining a higher degree over their jobs and adhere to their set boundaries (Kossek et al., 2006).

### 2.2.1 Leisure Domain

When it comes to leisure-time, previous research has shown that communication apps have been found to be closely linked to daily routines and leisure-time (Jeong et al., 2020), with users spending more time on these apps during the late evening or at night time - texting or scrolling through social media (Battestini et al., 2010; Bohmer et al., 2011). They are interconnected, and usage of one app often leads to prolonged usage of others, contributing to an increase of duration but also to an increased frequency of communication app checking (Heitmayer & Lahlou, 2021). The habit of frequently checking during the day, even when the smartphone is set to silent, is attributed to the FOMO on rewarding experiences that come as a result of the nature of communication apps - which is to offer cues through notifications (Oulasvirta et al., 2012).

These behaviour trends could be explained by the fact that users have more free time to spend on their communication apps during these leisure hours, fewer interruptions, or just having nothing better to do and so scrolling through the apps. Another fact is that the users are more likely to not be working or having other commitments at the time - in this way there is more leisure-time available to be spent engaging with their network via messaging or social media (Pielot et al., 2014). Another type of argument is the nature of the communication apps, that is that of providing the user with easy and immediate access to rewards, in the form of new content and information, hence keeping them engaged for longer periods of time during leisure-time (Marciano & Camerini, 2022). Not only that, but the social media apps have been shown to create an engagement of the user from one social media to another one. Studies have shown that participants who used one social media app were more inclined to use their smartphones to access other social media apps, resulting in extended usage beyond their specified time range (Marciano & Camerini, 2022).

Based on the aforementioned reasons in Section 2.1.1, research has already been conducted on the usage of smartphones together with communication apps, as well as the behaviour patterns that users create when using them during the leisure-time of the day.

The utmost observed behaviour patterns were pertaining to the continuous *checking habit* of the smartphone or communication apps that users tend to demonstrate daily. Individuals with this habit frequently check their smartphones, often without a specific purpose, but only to stay updated on notifications, messages, or other forms of communication (Oulasvirta et al., 2012). Others do so, just because it has already become a habit and their checking behaviour has started to happen unconsciously (M. Lee et al., 2018).

Another evident behaviour pattern has been in relation to the *amount of time* that users spend in different times of the day on their smartphone. According to research, people spend more time on their smartphones during leisure hours, such as evenings and weekends, than during working hours or other productive activities (Bohmer et al., 2011; Oulasvirta et al., 2012).

Yet another intriguing aspect is the *time of day* when these behaviours take place. Research has indicated that smartphones are most probably to be used by communication apps category at all hours of the day, but with a probability of 50.00% happening in the afternoon and evening and more specifically social media apps having the highest probability to be used in the late evening (Bohmer et al., 2011). On the other hand, in the early morning time frame, total smartphone usage is at its lowest and the communication apps usage is minimised. This occurs due to the fact that people spend more time in this period with other categories of apps - such as news or weather apps - instead of communication apps (Bohmer et al., 2011).

Additionally, texting has become a widespread form of communication in modern times, and the timing in which text messages occur has already been the subject of several studies. According to research, texting is an activity that is done more frequently at the end of the day (Battiston et al., 2016; Bohmer et al., 2011) - with the peak of text messages taking place between the 16 and 21 hours (Bhih et al., 2016). This aligns with the previous findings presented (Bohmer et al., 2011) and suggests that people are more likely to engage in texting during the late afternoon and early evening hours. One reason could be that people are more likely to be free from work or other commitments at this time and have more leisure time to engage in texting with their network. Additionally, it may also be driven by the need for social connection and communication with friends and family after a busy day (Pielot et al., 2014).

Apart from the time of day, the design of communication apps can also influence how long users engage with them. One argument is that communication apps offer users easy and immediate access to rewards, such as content and information, can keep them engaged for longer periods of time during leisure-time. For example, a messaging app that also provides quick access to news articles or other interesting content may be more likely to keep users captivated for longer than an app that only offers basic messaging functionality. When users feel that they are getting something valuable from an app, they are more likely to continue using it. This is because it motivates them to continue using the app and receive these rewards, which can in turn increase their overall usage in terms of duration when at leisure (Marciano & Camerini, 2022).

What is more, with regard to the extensive usage of communication apps, users have even attributed their delayed bedtime to engaging with social media and their network until they fall asleep (Kolhar et al., 2021) - thus impacting their sleeping schedule as well as their sleep quality and overall health and well-being (Thomée et al., 2011). This habit is accompanied also with the fact that they do not feel in control to stop using the apps and therefore continue to do so until the late hours of the night (Fu et al., 2021). Such behaviour could be a result of the nature of communications apps themselves which is to always give the user new and interesting content and possibilities to interact with their network - consequently keeping the users attached to them. Moreover, the design in which they are engineered is to encourage extended usage through the use of persuasive design techniques such as push notifications, social validation indicators, and addictive content (Oulasvirta et al., 2012).

Therefore, in the pursuit of better understanding the impact of communication apps on user behaviour, it is essential to focus on the communication habit patterns that users exhibit during leisure-time. By examining these patterns, researchers can gain valuable insights into how users interact with these apps and identify specific behaviour patterns that could be targeted for future intervention. Leisure-time is essential for understanding user behaviour since it is a time when people are free to engage in activities of their choosing without being constrained by work or other responsibilities. In conclusion, observing **communication habit patterns during leisure time** can provide a more accurate representation of how users engage with communication apps in their daily lives.

### 2.2.2 Work Domain

Within the work domain, technology can impact employees in various ways. Being surrounded by technology at the office has been identified as an impediment in achieving a good focus, due to its interrupting nature (Colbert et al., 2016). Before the era of instant messaging platforms at work, one of the main interrupters were emails. Allowing employees to be disrupted by regularly incoming information and email requests could make it difficult for them to maintain attention at complex or creative tasks that would require a great deal of effort (Jackson et al., 2001). In today's modern workplace, on top of the emails come the smartphones and instant messaging platforms which allow for real-time communication between work colleagues.

With the advent of home-office policies and remote work, employees started relying more and more on asynchronous communication which is represented by emails and instant messaging rather than discussing matters over a virtual call or just a coffee if they were to be in the office (Yang, 2021). This resulted in employees becoming heavily reliant on it, dissolving the line between human and technology, and thus creating a dependency. As a result, employees often feel compelled to act and perform at the same speed as their machines without giving thought on the urgency of the request (Porter & Kakabadse, 2006).

Smartphones are perceived as requiring availability around the clock, which can disrupt the crucial process of disengaging from work and recovery (Derks et al., 2015). Not being able to recover from work because of the constant connection has been shown to have a greater negative impact on the employees' well-being and health than the actual work demands (Sonnentag & Zijlstra, 2006). Nevertheless, some studies found out that smartphones can have a positive impact on the workplace as well. They are thought to improve productivity, enable more easy communication and offer support in making decisions (Kim et al., 2017; Schlachter et al., 2018).

Although technology is advantageous to the digital workforce and the modern workplace, its extensive use may have implications for how employees develop and express their personality, relate to others, and collaborate. Research indicates that technology's increasing pervasiveness has negative effects on identity development and expression (Colbert et al., 2016). Additionally, the observed effects on employees' communication and collaboration patterns are likely to have an impact on productivity and innovation in the long run (Derks et al., 2015) as they may find it more challenging to interact with other work colleagues and therefore have a hard time doing team work.

As a result of this technology abundance, employees started to feel technostress in the work-domain as well. For the consequences experienced by employees which were presented in Section 2.1.1 some organisations have already started implementing solutions. As a countermeasure to distress caused by technostress and the pervasiveness of technology, some organisations actively decided to lower their dependence on email, encouraging employees to meet personally at the office (Burkus, 2017), with the aim of improving complex task solving and better decision making (Colbert et al., 2016). The benefits of face-to-face interaction or virtual meetings where the work colleague can be seen and heard indicate an overall enhanced work performance and teamwork, when compared to asynchronous communication like email and instant messaging (Yang, 2021). With this in mind, it is clear that technostress is felt by the employees due to the hard time they have in handling such a high degree of technology at the workplace with one potential consequence being engaging in non-work-related activities during work-time as a countermeasure to the distress felt by technostress (Vitak et al., 2011).

A behaviour that has been causing reason for concern is cyberslacking, also referred to as cyberloafing. It represents the utilisation of technology, smartphones, and internet during work hours for non-work-related activities and personal use, and is on the rise within office domains (Jeong et al., 2020; McBride et al., 2015). According to a survey conducted by Cisco, a substantial majority of employees, to be more precise 83%, have acknowledged to engaging in technology use for personal purposes during working hours (Taleb Zaher, 2010). This has been shown to be more frequent within technology extensive workplaces where employees disclosed to use up a minimum of one hour per day on cyberslacking (Salary.com, 2013). Similar behaviour has been observed among students as well. A study showed that 40% of students spend time on non-study-related activities on the internet (Lavoie & Pychyl, 2001) with some of the preferred activities including checking emails and instant messaging (Madden, 2017).

Previous research tried to determine what are the reasons for engaging in cyberslacking. Vitak et al. (2011) identified that employees who perceive technology as a positive support means to perform their work were more likely to engage in this behaviour. What is more, this would lead them to be more socially active and communicate via instant messages or emails with their online social networks. Similarly, if the tasks at hand were very repetitive or would require a great deal of creativity, employees would turn to cyberslacking. Justification for this could be the positive effects it was shown to have, some of them being improvement of creativity, relief from fatigue and stress, and greater job satisfaction (Eastin et al., 2007; Reinecke, 2009).

A further reason that was investigated is job satisfaction. Results show that the less satisfied an employee is with their job, the more they would be inclined into performing activities like texting or using social networking sites (Vitak et al., 2011). This could be a coping mechanism to balance negative feelings experienced at work by immersing in social connection to fulfil themselves (Salehan & Negahban, 2013). Other reasons for engaging in cyberslacking could be the lack of motivation after the weekend, procrastination with the tasks at hand, or simply with employees' personality (Jeong et al., 2020).

Lastly, some may use cyberslacking as an adaptive strategy in response to a distress felt by technostress at the office (Khan & Mahapatra, 2017) and engaging in this type of activity can have long-term effects on employees by promoting compulsive behaviours and increasing technostress (Y.-K. Lee et al., 2014). Office workers who experience technostress were shown to be more likely to engage in non-work-related activities during work-time because it leads to less focus and therefore promotes cyberslacking (Güğerçin, 2020). Comparable is the case for college students. X. Li and Liu (2022) revealed that cyberslacking was favoured if technostress was experienced, and a link could be established between burnout and engaging in this type of activity.

As a result, employees use their smartphone during working hours for non-work-related purposes more and more. Despite employees and organisations being aware of the potential negative impact of smartphones on work productivity and the balance between work and personal life, their accessibility is growing on a daily basis (Jeong et al., 2020). Therefore, research was also conducted to understand if cyberslacking might be the outcome of habitual behaviour.

Garrett and Danziger (2008) could establish a relationship between the act of engaging in non-work-related activities at work if the employer had already formed a habit from using a computer. Additionally, internet addiction which is the result of an ingrained habit was also related to cyberslacking (Chen et al., 2008), thus implicating that people who lack self-control have higher chances to fall for this activity (Wagner et al., 2012), and conversely for people with a higher degree of restraint (Vitak et al., 2011). Nevertheless, organisations begin to express concern only when such utilisation results in diminished productivity or poses a security hazard by diverting employees' attention from their tasks (Stanko & Beckman, 2015). Lastly, considering the close association between work domains and smartphones nowadays, diminishing or prohibiting smartphone use at an employee level is not a pragmatic approach (Jeong et al., 2020). Therefore, organisations should be aware of the potential negative effects of technology on employees and implement measures to regulate its use (Yang, 2021).

To conclude, we discussed how technology impacts work and employees (Colbert et al., 2016; Kim et al., 2017; Porter & Kakabadse, 2006; Schlachter et al., 2018; Sonnentag & Zijlstra, 2006; Yang, 2021), and we addressed cyberslacking (Garrett & Danziger, 2008; Güğerçin, 2020; X. Li & Liu, 2022; Vitak et al., 2011; Wagner et al., 2012) and technostress (Burkus, 2017; Colbert et al., 2016; Yang, 2021) as potential negative effects of heavy smartphone usage, thus being a reason for concern. In the next section, the focus shifts on better understanding how technology - with special attention on smartphone usage - could lead to habit formation.

## 2.3 Habit Formation Theory and the Link to Smartphone Usage

The first contributions to the Habit Formation Theory were made by the philosopher William James who was stating that humans are essentially characterised by the sum of habits they have (James, 1983) and since then it has been researched and explored even further. A recurring definition states that "a habit is formed when exposure to the cue is sufficient to arouse the impulse to enact the associated behavior without conscious oversight" (Gardner & Rebar, 2019).

Later research discoveries provide foundation to understand how habits are driven by both the person and environment in which they are (Carden & Wood, 2018). This is because habits are thought to explain the consistency and stability of human behaviour over time, as they are formed on automaticity and can reveal why a person engages in a specific behaviour in similar situations. They help in dealing with complex tasks that require minimal cognitive effort. In the study of addiction, habit formation is a strong indicator of addictive behaviours development. In conclusion, habits are shaped by both internal and external factors, encompassing motivation, willpower, social norms, and the local and temporal context. Therefore, they constitute a fundamental component in understanding human behaviour (Wood & Rünger, 2016).

In a similar fashion, the Habit Formation Theory could be applied to smartphones as well since they have been described as being habit forming devices because of the "checking habit: brief, repetitive inspection of dynamic content quickly accessible on the device" (Oulasvirta et al., 2012). This means that a habit is formed when a behaviour is performed repeatedly within a given context (i.e cue) so that a linkage between the behaviour and the cue is developed. Once this is in place, the habit is triggered whenever there is exposure to the cue without conscious control by activating a representation of the habit from the memory (Strack & Deutsch, 2004; Wood et al., 2014).

One of the main reasons why smartphones can be considered habit-forming devices are notifications, which are the main function helping in habit formation (Renfree et al., 2016), and thus acting as signals or cues. What is more, it was shown that habit formation is accelerated when rewards are offered on interval schedules because they resemble natural resources which have seasonality. Therefore, receiving rewards on an interval basis will likely encourage habit formation by allowing context-response associations to form without considering the purpose or result of the action (Wood & Rünger, 2016). Likewise, regular notifications remind the user to conduct a habit repeatedly (e.g., check on social media) although the user might be using the smartphone for other purposes at that moment (e.g., browsing) (Carden & Wood, 2018). This is called conditioning, a process in which people learn to associate a stimulus or situation with a behaviour or response. To be more specific, in the context of habit formation and from the interval rewards perspective, we need to look at the operant conditioning process also called instrumental learning. This is based on the principle of repeated behaviours which are reinforced through rewards that are received once the action is performed. It means that people learn to associate a behaviour with the consequence they experience after performing it. If it is positive and pleasant, the likelihood to repeat it again is higher (Wood & Neal, 2007).

Lastly, attentional mechanisms are an influential factor in habit formation as the process of instrumental learning focuses the mind on situation cues and their rewards (Wood & Rünger, 2016). The more a behaviour is performed, the more it was found to tie in with the effectiveness of the habit (Rebar et al., 2016). Consequently, activities highly compensated receive a higher amount of attentional priority over neglected ones (Luque et al., 2017). This can be very easily translated to smartphone usage behaviour. Apps are designed to provide the user with an experience with each engagement. This can be in the form of a notification but also in the form of likes, views, points or added benefits if they ensure to regularly go back to the app.

For instance, the rule of immediate response to incoming notifications has been described as a necessity to stay connected, enforcing the idea of the checking habit (Holtgraves & Paul, 2013). Besides, it was found that people tend to keep their smartphone with them the whole time and frequently check it even if it is on silent mode, as they feel the necessity to stay in the loop or because it has already become a habit (Oulasvirta et al., 2012). In addition to that, it was shown that users have the habit of checking their phone first thing in the morning and as a last thing before going to sleep (Y.-K. Lee et al., 2014) - again reinforcing the idea of smartphones becoming a habit-forming device.

People also rely on habits because of external factors like stress, distractions, and time pressure. If a specific behaviour is associated with a component, the mental image of the learned reaction within that given situation is triggered whenever people experience distress. This makes it easier for people to continue engaging in a habit, be it either good or bad. Under these circumstances, people tend to engage in undesirable behaviours as often as 6 times a week during their daily routine, especially when the focus is elsewhere (Wood & Rünger, 2016). One main distraction in such situations could be the smartphone which can foster an unhealthy dependency, thus alluring the user to engage in a vicious cycle. To overcome such pitfalls, some choose to wilfully reorganise their environments to minimise enticements, put away their smartphones, and eliminate cues to avoid any distractions (Carden & Wood, 2018). Nonetheless, this requires a certain degree of self-control and can be very hard to overcome.

In essence, one of the main problems we identify is that smartphones lead users to unconsciously forming new behaviour patterns which in turn transform into habits after sufficient repetitive usage. As previously mentioned, these habits can have a negative impact on users' daily life as these could distract and interrupt them from performing their regular activities and therefore add more unnecessary stress (Hattingh et al., 2022; Thomée et al., 2011). The key obstacle is that habits continue to be unintentionally triggered by recurring cues in the environment (Walker et al., 2015) thus, individuals with well-entrenched habits process information in a manner that decreases the probability of considering alternate actions (Wood & Rünger, 2016). Accordingly, the context and environment of the user could also be imperative in influencing habit formation (Y.-K. Lee et al., 2014; Walker et al., 2015). Therefore, we believe it is necessary to identify how habit-forming smartphone communication patterns are shaped within the context and domain, particularly with regard to work-time and leisure-time.

## 2.4 Smartphone Communication Patterns

### 2.4.1 Overall Patterns

Having discussed habit formation in everyday life within the context of smartphone usage, the focus shifts now onto the habit-forming patterns that users cultivate by using smartphone communication apps in the work and leisure domains.

In the literature, these behaviours were determined by analysing data mainly in form of self-report questionnaires and/or log-files from smartphones (Ferreira et al., 2014; Holtgraves & Paul, 2013; Jeong et al., 2020; Monge Roffarello & De Russis, 2022; Oulasvirta et al., 2012). The outcome of this examination led to the rise of smartphone usage patterns. For their evaluation different measures like frequency and duration of use, number of screen touches, repetitive app checking, app-switching behaviour, and apps usage sessions were employed. In the following, an overview of the recurring smartphone usage patterns will be presented with the aim of providing a better understanding on how these emerge and how they are analysed.

#### Usage Patterns based on Duration

To determine smartphone usage patterns with duration of smartphone usage is the most common approach. This is because the amount of time one spends on the device is the first indicator for a potential overuse that could lead to further consequences like technostress (Butts et al., 2015; Khan & Mahapatra, 2017), addictive behaviours (Duke

& Montag, 2017), work addiction (Porter & Kakabadse, 2006), or being a link to time misuse (Lin et al., 2015).

When it comes to the findings about the duration of smartphone usage there are several studies that present different results. For example, according to one research it was estimated that the average daily duration of smartphone usage is roughly 59 minutes per day and of an app session 71.56 seconds (Bohmer et al., 2011), while another study claims that the average daily usage duration is 160 minutes (Montag, Błaszkiewicz, Lachmann, et al., 2015), and yet another states that the average daily smartphone usage time was more than 2.5 hours (Deng et al., 2019). The difference of these results could be explained by the difference of the year in which each study was conducted and written - thus also noticing the increase in the duration of smartphone usage year by year. On the other hand, research from 2022 shows that even though the overall usage of smartphones has increased, the time spent for one smartphone session seems to decrease resulting in a median of only 56.73 seconds (Monge Roffarello & De Russis, 2022).

By investigating the amount of time spent on the smartphone, previous studies have shown that scrolling through apps occurs primarily in the afternoon and in the evenings (Oulasvirta et al., 2012). This suggests that smartphone usage may be higher during leisure-time or after working hours. Additionally, studies have revealed, that users tend to spend more time on their smartphones during the late evening or at nighttime (Battestini et al., 2010; Bohmer et al., 2011) - especially the young adults (Deng et al., 2019).

Focusing on duration of use during work-time, Jeong et al. (2020) determined that the longest duration of use which accounts for over 60% was noticed when users were using their smartphones for non-work activities during work-time. They found that the average session lasted for 333 seconds, with 659 out of 1925 sessions taking place during working hours. In their study, the longest sessions of smartphone usage also occurred when users were at work. By investigating the timing of non-work-related sessions during the work week it was identified that employees tend to engage in more non-work activities on Mondays and Tuesdays, with a drop on Wednesdays and a slow increase towards the end of the week. Non-work engagement was higher after 12 on all days except Friday. In contrast, smartphone usage for work-related activities was low on Mondays and Tuesdays, with a slight increase for the rest of the week. Employees used their smartphones for work in the first part of the day throughout the week, but engagement in work-related activities was very low compared to non-work activities.

In addition, a vast number of studies have been conducted on users' subjective perceptions of smartphone usage. On one hand, participants were found to overestimate their app usage, particularly in popular app groups such as social networking, media, utilities, and web browsers (Deng et al., 2019). Likewise, a recent study found that participants tend to overestimate the time spent on social media platforms, with more accurate estimations for Instagram use rather than WhatsApp or Snapchat (Verbeij et al., 2021). This overestimation may reflect a high degree of smartphone integration into people's everyday life, in which each activity is linked to a particular app and suggests that people may have different perceptions of the duration of usage depending on the app they use. On the other hand, Duke and Montag (2017) investigated the relationship between smartphone addiction and self-reported work productivity and found that users spend more time on their smartphones than intended during work hours. The participants' subjective data showed that this time they underestimated their smartphone usage compared to log data from their devices, which may be due to time distortions experienced. This could be because increased cognitive burden caused by increased smartphone use may reduce the likelihood of correct estimation of use time (Deng et al., 2019). In conclusion, both overestimation and underestimation are a common issue in research as one study identified that the degree of misinterpretation was positively correlated with actual use, indicating that people may not be aware of their true smartphone usage (Lin et al., 2015).

### Usage Patterns based on Smartphone Checking

Apart from duration, the next measure that receives a lot of attention is the frequency at which users are checking their smartphone. This has been researched with a particular high interest out of various reasons. Firstly, because it provides insight into which apps are favoured, and what type of notifications are reacted to. Secondly, because temporal and local context offer information when and where specific apps are preferred (Ferreira et al., 2014). Lastly, it represents a key element in studying smartphone usage behaviour and its possible implications on users' life and well-being (Tossell et al., 2015).

As already mentioned in the previous section, although duration increases overall, users spend less time for each app session (Monge Roffarello & De Russis, 2022) which indicates that they must repeat themselves very often during the day to make up for the overall time spent. Bohmer et al. (2011) disclosed in their study on basic and contextual app usage that users actually spend on average less than 72 seconds with an app at a time which would require at least 60 checks per day to result in the one hour total duration measured by them. Similarly, Yan et al. (2012) discovered that half of the total duration of smartphone usage consists of short checking sessions which last less than 30 seconds. When comparing to laptop usage sessions, Oulasvirta et al. (2012) observed that these happen 4.60 times less than on smartphones. Moreover, it was classified as an annoying checking habit which can lead to the overuse of smartphones and difficulty in self-control. This exposes the rewarding design of apps due to the notifications feature that most laptop operating systems used to lack at the time of the study.

Alike to the checking habit described above (Oulasvirta et al., 2012), the concept of micro-usage was coined by Ferreira et al. (2014) being defined as "brief bursts of interaction with applications". They determined that micro-usage appears with 41.50% probability in all apps and users. What is more, communication apps accounted for the most micro-used and were favoured for engaging in this type of behaviour. The reasoning behind this lies in their nature of regularly providing notifications and rewards. Lastly, they tried to identify what is causing this behaviour. What was observed is that 62% was initiated by incoming notifications while 18% due to "killing time" when at home or alone. This can explain why the frequency of interactions rather than the duration of use turned out to be associated with signs of addictive behaviour (Shin & Lee, 2005). Lastly, this adds to the research findings from (Salehan & Negahban, 2013) which identifies that social media use is a significant predictor for smartphone addiction, and reinforces the assumption that loneliness felt by users increases usage.

#### Usage Patterns based on App-switching Behaviour

Yet, another type of pattern is focusing on the app-switching behaviour. These types of patterns try to identify how and why users jump from one app to another while using the smartphone. Of particular interest, it is to find out if the users are led from one app to another, engage in this behaviour because of the various notifications on their screen (Shin & Lee, 2005), or do this because of a given context (Jeong et al., 2020; Monge Roffarello & De Russis, 2022). Furthermore, studies try to identify potential consequences (Porter & Kakabadse, 2006).

Jeong et al. (2020) analysed smartphone log data of 18 participants trying to identify how they behave in the work and non-work domain. By including additional subjective data from surveys, four types of behaviours were analysed: "non-work-related behaviors during work time, work-related behaviors during work time, work-related behaviors during non-work time, and non-work-related behaviors during non-work time". The results show that on average the app-switching behaviour occurs 5.16 times per session, and the longest sessions with the highest app-switching behaviour appeared during work-time when users engaged in non-work-related smartphone activities. Moreover, communication apps were used to the highest degree for such behaviour. One issue identified with the excessive usage of technology is work addiction. In their study, Porter and Kakabadse (2006) detected that work addiction is enabled by technology use within the organisation and has the same effects outside of it. Hence, this can cause employees to sacrifice other private commitments they have and vice-versa.

Monge Roffarello and De Russis (2022) identified under what circumstances do users switch between apps. The results from the analysed log data indicates that over 40% of smartphone activity includes a switching behaviour of at least 2 apps which can be connected to the context the users find themselves in. The highest rate was identified when sitting in a specific place (local context), followed by business days (temporal context). On the other hand, the most common period among users was in the morning between 6 and 8. This finding reinforces that smartphone habitual behaviour is created when associating an activity with a context, especially if it can be tied to a repetitive behaviour like a morning routine (Ferreira et al., 2014). Lastly, once again, communication and social network apps were the most popular when engaging in app-switching behaviour (Monge Roffarello & De Russis, 2022).

#### Usage Patterns based on Revisitation Behaviour

The user revisitation patterns focus on how many times a user revisits the same app within a given period. The interest in analysing such practice derives from the web browsing behaviour (Jones et al., 2015). The goal of these patterns is to identify how users communicate through smartphone apps (Holtgraves & Paul, 2013), if the users can be portrayed based on their revisitation behaviour (Jones et al., 2015) and how the purpose of an app influences how often a user accesses it (Tian et al., 2020).

In their study, Jones et al. (2015) investigate two revisitation patterns: a) for a specific app within a predefined time, and b) for a singular user taking into consideration the span between any app-launch on the smartphone. The results conclude that communication and social networking apps are the most popular ones used in revisitation patterns as well. For WhatsApp chances are that a user will revisit the app again within 2-4 minutes after initial usage with a probability of 16%. This may be due to users starting a conversation and revisiting the app whenever they get a reply, and also checking if the message sent was received and read. The users' revisitation patterns were categorised into three types: *Checkers*, who engage in a fast revisitation (less than an hour) and account for 44%, *Waiters*, who revisit in intervals between one minute and four hours in a proportion of 46%, and *Responsives*, who have an irregular re-visitation pattern and make up for 10% of the participants in the study. These results were obtained from a group of 165 participants (Jones et al., 2015). Based on the findings, it can be noted that instant messaging and the design of communication apps attract users to constantly check them with the possibility of becoming prey to the immediate response rule (Holtgraves & Paul, 2013).

For the purpose of improving app behaviour for first time users by looking at behavioural patterns, another research employed the revisitation pattern for 5000 users obtaining very similar results for Checkers (39.60%), however with a high discrepancy at Waiters who accounted only for 13.50%, and finally Responsives for a surprising 46.80% (Tian et al., 2020). Obtaining different results from the previous study reveals how disparate users are but also how much the size and characteristics of a study can influence the evenness of behaviour patterns. Furthermore, this bolsters how important it is to study users behaviour as it can help identify a range of insights which could be useful in various domains.

As seen, smartphone usage patterns can be identified and analysed based on various metrics and approaches, all with the goal of better understanding user behaviour, identifying potential risks and solutions to users' life and well-being, as well as for the purpose of better designing apps. However, up to now most research has been conducted on smartphone usage overall with little research examining solely communication apps in the context of work-time and leisure-time. Therefore, it would be of interest to derive smartphone usage patterns in both domains and draw conclusions on similarities and distinctions between them. Lastly, for the purpose of this work, the focus lies in the frequency of communication app checking, the relationship between duration and frequency, and other potential patterns that may emerge from data analysis.

#### Usage Patterns during Leisure-time & Work-time

Considering the aforementioned habit-forming smartphone usage patterns as well as the impact and consequences of smartphone usage during leisure-time and work-time discussed respectively in Sections 2.2.1 and 2.2.2, this work will investigate the **smartphone usage patterns** with regard to **communication apps** that users engage in during **leisure-time** and **work-time**.

One interesting point would be to discover how the user app checking behaviour is developed during both domains. The frequency at which users check their communication apps is an important aspect to consider when examining their behaviour along with how they prioritise communication activities during their free time and working time.

Another interesting aspect of studying communication app usage during leisure-time and work-time is to investigate whether there is a link between users' app checking behaviour and the amount of time they spend on these apps overall. This could involve exploring whether users who check their communication apps more frequently also spend more time on these apps or whether there is no association between these two variables. Understanding the relationship between app checking behaviour and overall app usage in terms of duration can provide insights into the underlying factors that drive its excessive use. Alternatively, if there is no association between these variables, this may suggest that users' app checking behaviour is not a reliable predictor of their overall app usage.

### 2.4.2 Leisure-time Usage Patterns

#### Usage Patterns based on Smartphone Checking

In terms of the frequency of app checks, or the checking habit, various studies have been conducted for smartphone checks in general. These short, scattered usage sessions or "checking behaviours" (Oulasvirta et al., 2012), are one of the most visible patterns of smartphone use (Deng et al., 2019). We believe that the findings will be consistent with the nature of communication apps, which is to provide continuous new content from one's social network and to deliver it in an attention-capturing way. The use of rewards in the communication app design can also be used to increase engagement and motivate users to use it more frequently. For example, an app may offer badges, points, or exclusive content for completing certain tasks or achieving milestones within it. This creates a sense of achievement and rewards users for their continued engagement, thereby extending the overall usage duration.

Keeping this in mind, we expect that the frequent check of the smartphone happens because of communication apps and less likely because of other category of apps (e.g. music, video-streaming, gaming, entertainment, shopping, lifestyle etc.). Moreover, the rise of smartphones and messaging apps has made texting more convenient and accessible than ever before. This has led to an increase in texting frequency, particularly among younger generations who tend to prefer texting over other forms of communication such as phone calls or emails (Battestini et al., 2010).

From the findings of various research, important to mention is that users have been observed to check their smartphones often, via brief app checks, lasting between 10 to 250 seconds (Bohmer et al., 2011; Falaki et al., 2010). These observations suggest that the use of smartphones has become a habitual behaviour that occurs with a remarkable regularity over extended periods of time (Battiston et al., 2016). Additionally, it was shown that users tend to stay more frequently on short sessions with only one app rather than longer sessions with several apps (Bohmer et al., 2011).

In a study it was found that short checking sessions, lasting less than 30 seconds, constituted half of the total duration of smartphone usage (Yan et al., 2012). This means that users were frequently engaging with their devices for brief periods of time, rather than extended sessions. Furthermore, another research conducted revealed that it was the frequency of smartphone interactions, rather than the duration of use, that was associated with signs of addictive behaviour. In other words, it was the habitual nature of smartphone use, rather than the amount of time spent using the device, that was linked to problematic usage patterns (Shin & Lee, 2005).

While this checking habit happens more than 30 times per day according to one study (Paasovaara et al., 2010), another research showed that users exhibit more than 300 times of unconscious checks per day (M. Lee et al., 2018). Indeed, the drastic increase in the number of checks in a day from one study to another could be due to the number of participants of the studies and their demographics, but could also be explained by the year gap between the two studies - demonstrating that the checking behaviour keeps increasing over time.

Even though some of the findings stated above are regarding smartphone usage only, several studies have consistently shown that communication apps dominate smartphone usage during leisure-time. It has been reported that in this domain communication apps take the largest percentage of app time consumption with regard to the total time of smartphone usage and other categories of apps. This suggests that people are more likely to use their smartphones for communication purposes during their leisure-time, which may be driven by their social and interpersonal needs (Deng et al., 2019; Montag, Błaszkiewicz, Sariyska, et al., 2015). This is why this work makes another assumption that these habit patterns could be very much similar to the communication behaviour patterns as well.

The rationale behind the checking habit is a crucial aspect to consider, and it has been found that the capturing nature of communication apps plays a significant role. Communication apps use cues - in the form of new messages or content via regular notifications - which attract users by providing them with new messages or content updates at regular intervals. Notifications aim at maintaining a constant interaction of the user with the communication apps out of FOMO on important updates or news from the social network. This creates a sense of immediacy and urgency, thus leading users to check their smartphones frequently in order to stay up to date with the latest information. All of that is already supported by studies which have shown that communication apps are the first thing that people will check as soon as they wake up in the morning (Bohmer et al., 2011) as well as right the last thing they check before they sleep at night (Montag, Błaszkiewicz, Sariyska, et al., 2015).

Another notable aspect of users' habits with regards to checking their smartphones is that they tend to frequently check their communication apps during the day, even when their smartphones are set to silent mode (Oulasvirta et al., 2012). Moreover, this habit of immediately responding to notifications is known as the immediate response rule (Holtgraves & Paul, 2013), therefore even silencing the smartphone will not help in avoiding notifications from the communication apps. This behaviour could be attributed to the FOMO on what are perceived as rewarding experiences. In fact, a study has linked this impulsivity and the perceived necessity of instantly checking incoming notifications to the FOMO on rewarding experiences. It is worth mentioning that this behaviour may have negative consequences, such as distractions and decreased productivity (Marciano & Camerini, 2022).

Interesting findings also were reported with regard to users checking their smartphone and describing it as "feeling natural or automatic, and even unconscious like when you cough and put your hand over your mouth" (Heitmayer & Lahlou, 2021). This implies that smartphone checking has become so embedded in their daily habits that it happens almost unconsciously. Moreover, another study has revealed that a majority of smartphone interactions, approximately 89% of them, are originated by the users themselves rather than being triggered by notifications. Therefore, this indicates that the disruptiveness of smartphones has been founded by the users' behaviours and not anymore by the smartphones (Heitmayer & Lahlou, 2021).

Another striking habit pattern was that of users participating in fidgeting-behaviour, meaning making small movements with their smartphone due to impatience or simply boredom. Users may pick up their smartphones, unlock them, use them briefly, and then put them aside without any particular goal in mind (Heitmayer & Lahlou, 2021). Furthermore, it could be the case that a cycle of an unintentional check of the communication apps would cause the users to fall into a loop of going from one communication app into another - consequently spending more time than they had originally planned (Heitmayer & Lahlou, 2021).

Moreover, adding to the importance of analyzing the communication apps, it has been found out that the patterns of communication frequency via smartphones tend to reflect the human daily rhythm (Battiston et al., 2016). Studies have shown that each user's frequency habit on communication apps displays a distinct daily pattern that is persistent over time and that contains a component intrinsic to each unique individual (Battiston et al., 2016) and the frequency of checking these apps has not shown significant change across seven days of a week and between weekdays and weekends. These results indicate that checking communication apps on a regular basis has become a rooted and habitual behaviour in users' daily routines. These habits have become so deeply ingrained that they mirror each individual's daily rhythm, suggesting that smartphone use, and most importantly the communication apps, have become an essential part of the users' daily routines (Deng et al., 2019).

Regarding the users' self-perception of their smartphone usage, Marciano and Camerini (2022) examined how users perceive their smartphone usage in terms of time spent on a typical weekday and weekend day. The study yielded intriguing findings, as it revealed that users tend to rely more on the frequency of their checking behaviours rather than estimating the actual time spent on their smartphones. This means that their perception is less based on the total duration of usage, and more centred on how often they use their smartphones throughout the day. This insight sheds light on how users view their smartphone usage, which has important implications for understanding the potential addictive nature of smartphone usage and developing strategies to reduce the negative impact on users' well-being.

All of the above mentioned checking behaviours of communication apps could potentially lead to habitual patterns of usage that may become difficult to control over time as it has been reported by users themselves (Tossell et al., 2015) - and over time turn into addiction. This is due to the fact that communication apps are engineered in such a way to encourage prolonged usage by employing tactics such as infinite scrolling, which lacks any clear stopping points, and notifications or daily rewards that remind users to reopen the app (Noë et al., 2019). These findings highlight the importance of examining the frequency of communication apps usage as a key aspect of smartphone excessive usage.

As the above-mentioned research indicates, the frequency of communication apps usage does not occur during specific periods of time but rather throughout the day, most of the time without a purpose. Each user's frequency of using communication apps demonstrates a distinct daily pattern that remains consistent over time and contains an inherent element specific to the individual. Therefore, the objective of this work is to determine that **the frequency of communication apps activations varies from day to day during leisure-time**. In this way, by understanding how these habitual patterns of smartphone checking occur, this work can contribute to developing strategies to reduce their impact on individuals' well-being.

#### Relation between Duration of Use and Smartphone Checking

Having discussed both aspects - duration and frequency of communication apps - during leisure-time separately, it is now important to examine the relationship between them.

As already stated from previous studies, users spend a considerable amount of time on communication apps during leisure-time (Montag, Błaszkiewicz, Lachmann, et al., 2015). With it comes as well the checking habit - brief usage sessions repeating over time - which has been shown to have an impact on the overall use of these apps (Oulasvirta et al., 2012). Additionally, the pattern of app re-visitation supports the idea that with every visit of the communication app the user will also stick around it for some time (Jones et al., 2015) or even fall into the loop of going from one communication app to another (Heitmayer & Lahlou, 2021). These findings highlight the interplay between duration and frequency of communication app usage during leisure time, indicating that habitual checking behaviours and revisitation patterns can significantly influence overall app usage.

Recent research has shed light on the relationship between problematic smartphone use and the frequency and duration of smartphone usage. Interesting studies revealed that even on an atypical day, there was a significant correlation between the traced frequency of usage and the self-reported duration, which was linked to problematic smartphone use. Moreover, the studies found that on a typical day, the self-reported duration of smartphone use positively and significantly correlated with the traced frequency of use, suggesting a strong relationship between these two variables. Particularly, traced frequency of use appears to be a more reliable predictor of problematic smartphone use than self-reported duration of use, which could be biased or inaccurately reported (Deng et al., 2019; Marciano & Camerini, 2022). By understanding the complex interplay between these two variables, researchers and clinicians can better assess and treat individuals who may be at risk of developing problematic smartphone use.

The relationship between problematic smartphone use and various smartphone usage metrics has been extensively studied. A study conducted on an adult population found that problematic smartphone use is related not only to the hours of smartphone use per week but also to the quantity of calls and text messages received and sent. This indicates that individuals who engage in excessive usage behaviour, as indicated by problematic smartphone use, tend to not only spend more time on their smartphones but also have higher levels of interpersonal communication through their devices (Montag, Błaszkiewicz, Lachmann, et al., 2015).

Similarly, other studies have highlighted the correlation between frequency and duration of smartphone use and problematic smartphone use. In fact, research suggests that individuals who are addicted to smartphones tend to spend twice as much time on their devices as non-addicted users and also interact with apps twice as often (Tossell et al., 2015). This underlines the interdependent nature of frequency and duration in predicting problematic smartphone use and not only.

According to Deng et al. (2019), there is a positive correlation between the amount of time spent each day using a smartphone and the number of app switches made by users. This suggests that people who use their smartphones more frequently also tend to switch between various applications more frequently. Additionally, the study discovered that social networking and conversation apps are the ones to which these app changes can be accounted most frequently. Overall, these results suggest that people who spend more time on their smartphones are also more likely to use social networking and communication apps more frequently, and that the two variables of duration and frequency may be mutually reinforcing.

Building on previous research, the discovery that communication apps are frequently used emphasises the need to understand the influence of habitual smartphone use on overall smartphone usage. This finding implies that regular usage of a limited subset of frequently used apps (e.g., social networking and communication apps) may result in the formation of "gateway habits" that increase overall smartphone usage (Oulasvirta et al., 2012). Such gateway habits may be difficult to break, leading to excessive use and negative effects on well-being. Also, the interdependent nature of frequency and duration in predicting problematic smartphone use and the positive correlation between smartphone usage and the number of app switches made by users (Deng et al., 2019) suggest that the two variables may be mutually reinforcing.

Essentially, frequent and periodic use of specific apps can contribute to the development of patterns of smartphone use that become deeply ingrained and difficult to change, potentially leading to addiction. Thus, it is critical to gain a deeper understanding of how habits form and how they may be disrupted to promote healthy smartphone use.

In reviewing the two aspects of duration and frequency of communication app usage during leisure-time, we can make the logical assumption that each time a user engages with an app, they are likely to spend a certain amount of time involved with it. This is primarily due to the fact that during leisure-time, users have more access to use their smartphones without disruption, which can lead to extended times of interaction with communication apps. For example, if a user receives a notification from a communication app, they are likely to react to it and thus spend time interacting with the app. This is due to users having more time to spare in the leisure domain, which may include spending more time on their smartphones.

As a result, we can anticipate that the **frequency and duration of communication apps will relate with one another, during the leisure hours.**

### 2.4.3 Work-time Usage Patterns

#### Usage Patterns based on Smartphone Checking

On one hand, research shows that very often users check their smartphone without having any notifications received. This happens as often as 300 times per day, without being conscious about it (M. Lee et al., 2018). Such a behaviour indicates that users formed an innate habit that can eat up their time or distract them from focusing with the tasks at hand (Jeong et al., 2020). What is more, it can also lead to feelings of frustration or self-doubt if there are no new notifications from the last check. Out of FOMO, users adopted a checking habit (Oulasvirta et al., 2012) that can be also described as the immediate response rule (Holtgraves & Paul, 2013) - before missing any notifications, it is better to check more frequently than to let someone wait.

On the other hand, another study detected that communication apps' notifications are the main reason why users check their devices. It analysed the number of notifications users get on their smartphone, and noted that 78.40% of them are received during weekdays with instant messages and email being at the top (Pielot et al., 2014). This adds on the findings from Ferreira et al. (2014) which identified that 62% of smartphone usage is initiated by incoming notifications of communication apps. Furthermore, when looking at the notification distribution during a day, it could be observed that there is no regular pattern to when these are incoming, for both email and instant messaging, indicating that they are triggered either by the app or by the person being contacted by. Besides, the response time from receiving a notification until it was replied to was twice as fast during weekdays compared to weekends (Pielot et al., 2014). These results reinforce the FOMO users experience, hence adhering to the immediate response rule (Holtgraves & Paul, 2013), and could also mean that users feel the need to act as fast as the machines (Porter & Kakabadse, 2006), hence replying to notifications at the moment of their arrival.

Apart from that, FOMO and the need to act as fast as the smartphones could lead to micro-usage due to the system design of communication apps (Ferreira et al., 2014) and could make users unaware of the actual time spent on communication apps. Duke and Montag (2017) conducted a study with the aim of linking smartphone addiction to a lower self-reported productivity at work. It was disclosed that users substantially underestimate the frequency at which they check their smartphone. These results were obtained by comparing diary entries from users with log data from their devices. Additionally, it was shown that users engage in a mechanical unconscious process which results in the checking habit (Oulasvirta et al., 2012) and have the tendency to pursue it during working hours as well, thus having a negative impact on their work related productivity (Duke & Montag, 2017).

Another behaviour that could affect productivity at work is cyberslacking. One study focused its attention on analysing how often and for how long during work-time employees use their smartphone for non-work and work-related purposes. It determined that 85.04% of the time it was used for non-work whereas only 38.16% for work related activities, highlighting that most of the usage could be categorised as cyberslacking (Jeong et al., 2020). This could mean that users engage in this type of activity as a countermeasure to the distress felt by technostress within the work domain, thus using their smartphone as a technostress inhibitor and engaging in non-work-related activities (Khan & Mahapatra, 2017) by checking their social media, communicating with their dear ones, or just ensuring they are up to date with what is happening outside of work. What is more, for non-work usage during work-time, it was found out that most of the time users engage in brief sessions lasting less than five minutes. For sessions that last longer than 10 minutes the number almost halved. Similarly, for work related smartphone usage during work-time, employees would rather use it in up to five minutes sessions compared to longer sessions lasting over 10 minutes, where again the number of sessions halved. Furthermore, it was determined that the probability of sessions occurrences throughout a day is unbalanced for both categories (Jeong et al., 2020). One reason for this could be engaging in a micro-usage behaviour which was triggered 18% of the time due to not having anything else better to do and thus just "killing time" (Ferreira et al., 2014).

Considering all this, it can be posited that it is still unclear whether users check their smartphones without a specific reason (M. Lee et al., 2018) or due to incoming notifications (Ferreira et al., 2014; Pielot et al., 2014) by adhering to the immediate response rule out of FOMO (Holtgraves & Paul, 2013), due to "killing time" (Ferreira et al., 2014), or as a potential technostress inhibitor (Khan & Mahapatra, 2017). As a result, users engage in a checking habit (Oulasvirta et al., 2012) which promotes a micro-usage behaviour (Ferreira et al., 2014) that has been shown to not follow a regularly occurring pattern. Lastly, it is a common phenomenon for people to not explicitly plan moments of stress, a desire to pass time, boredom, or loneliness, or when they want to receive notifications or not. Out of these reasons, we foresee that **the frequency of communication apps activations varies from day to day during work-time.**

#### Relation between Duration of Use and Smartphone Checking

Previous research exposed how users engage with their smartphones on a regular basis. In terms of duration, users use up to almost three hours from their day with activities on their smartphone, engaging in work and non-work activities during work-time (Jeong et al., 2020), texting their dear ones (Salehan & Negahban, 2013), responding to notifications or simply scrolling out of boredom (Montag, Błaszkiewicz, Lachmann, et al., 2015; Oulasvirta et al., 2012). However, in terms of frequency, which represents the checking habit (Oulasvirta et al., 2012) that promotes a micro-usage behaviour (Ferreira et al., 2014), it takes them less than one minute to have a quick look at updates which were received since the last check (Yan et al., 2012) allowing them to perform this activity very often during the day.

Putting the two variables - duration and frequency - into relation during work-time, a study which analysed types of smartphone usage behaviour during work-time determined that the more sessions a user engages in, the more time is being spent on the smartphone. Specifically, for cyberslacking activity, out of a total number of 477 sessions, the average time spent in a session was 403 seconds, whereas for work related usage during work-time, out of 182 sessions, the mean identified was only 263 seconds (Jeong et al., 2020). The results of the study indicate that cyberslacking is the preferred activity for engaging with the smartphone, and thus involve more time and more checks during work-time. A potential cause for this could be the design of the communication apps (Ferreira et al., 2014) which intends to keep the users engaged for as long as possible. This could lead to what Duke and Montag (2017) call time misuse, and was shown to be a reason for concern, as users underestimate the amount of time they spend on their devices, and was linked to lower productivity at work because of increased usage.

Additionally, to the identified behaviour of cyberslacking and work-related smartphone usage, a further finding from Jeong et al. (2020) was that the distribution pattern of usage time did not show any statistically significant deviation from the distribution pattern of session counts. In other words, there was no identifiable change in the tendency for usage time to be brief despite a high number of sessions, or for total usage time to be comparatively lengthy despite a small number of sessions. Even though this may be different when looking only at particular app sessions, when it comes to the overall duration and frequency, a relation between them could be observed. As a result, it indicates a relationship between the frequency and duration of smartphone usage during work-time.

Further features that could indicate a relationship between the amount of checks and the smartphone usage time are notifications. By identifying that the response time to an incoming notification is under four minutes during weekdays, and over 70% of them arrive during weekdays compared to only 21% during the weekend, it could be established that the more notifications users receive, the more often they engage in replying to them, and thus contributing to the extension of the overall usage time (Pielot et al., 2014). Similarly, Ferreira et al. (2014) disclosed that most engagements are initiated by incoming notifications rather than the users themselves, with a response time which was two times faster in contrast to weekends. This can be the result of users feeling the urge to act as fast as their smartphones (Porter & Kakabadse, 2006) out of FOMO by adhering to the immediate response rule (Holtgraves & Paul, 2013). Furthermore, for work-related engagements, a potential explanation could be the organisations' expectations to reply promptly to incoming requests (Davis, 2002) which could take up more time than intended, hence contributing to an increase in duration.

Lastly, an increase in asynchronous communication could also affect the relation between duration and frequency. Yang (2021) has observed that the total number of unplanned calls in video or audio format, as well as the number of instant messages drastically increased after switching an entire organisation to remote work, affecting especially managers compared to regular employees, leading to an overall increase of work-time during a week. Nevertheless, written communication was shown to be favoured. Taking into consideration the nature of communication apps, prompting users every time there is an update, and many engagements being triggered by incoming notifications (Ferreira et al., 2014), the increased volume of asynchronous communication could also lead to a respectively high frequency of checking.

Overall, it may be said that cyberslacking is the most favoured behaviour among users during work-time, showing the highest amount of sessions and overall time spent in contrast to work-related activities performed on the smartphone (Jeong et al., 2020). The reasons for engagement are the design of the system (Ferreira et al., 2014), the high volume of incoming notifications (Ferreira et al., 2014; Pielot et al., 2014), the pressure to be available at all times (Davis, 2002), or simply a high workload (Yang, 2021). As a result, users adhere to micro-usage behaviour (Ferreira et al., 2014) and immediate response rule (Holtgraves & Paul, 2013) which could lead to time misuse (Duke & Montag, 2017), and hence spending more time with each notification than intended, contributing to an increase of duration with every app check. Out of these reasons, we believe that **frequency and duration relate with each other, during working hours.**

## 2.5 Summary and Research Questions

This chapter explored how habit-forming smartphone communication patterns are developed, their characteristics, what impacts them, and how they may affect a person's daily activities. As already mentioned, the widespread usage of smartphones has influenced the way people communicate and access information in both leisure and work domains. The ease of access to these apps, their repetitive use, the need to be constantly connected to friends, family, colleagues, and social networks can lead to habit-forming behaviours associated with communication apps usage in the leisure domain. Similarly, for the work domain, the pervasiveness of smartphones has raised availability (Davis, 2002) and performance (Porter & Kakabadse, 2006) expectations, and influenced the way of working (Kane, 2015). What is more, cyberslacking behaviour at the workplace affects employees' productivity and is a reason for concern for the employers (Jeong et al., 2020).

As a result, different patterns of communication app usage have been identified, including duration of use, checking behaviour, app revisitation, and app switching. Duration of use refers to the amount of time spent on communication apps (Deng et al., 2019; Montag, Błaszkiewicz, Lachmann, et al., 2015), while checking behaviour refers to the frequency of checking for new notifications or content (Bohmer et al., 2011; Oulasvirta et al., 2012). App revisitation refers to the tendency to repeatedly return to the same apps (Jones et al., 2015; Tian et al., 2020), and app switching involves switching between different communication apps (Jeong et al., 2020).

It is important to note that the formation of habits regarding communication apps can be influenced by the context in which smartphone usage occurs (Ferreira et al., 2014; Heitmayer & Lahlou, 2021; Jeong et al., 2020), including the split between work and leisure time. Understanding the patterns of communication app usage and the factors that influence habit formation can provide valuable insights for designing interventions and strategies to promote healthy smartphone usage behaviours.

All in all, there seem to be some limitations in the research that has already been conducted since there has not been any work done on the way that the user behaves during leisure-time or work-time specifically with regard to behaviour patterns of communication apps usage. The research has mainly been spread in relation to smartphone usage rather than in relation to communication apps only and not making a clear distinction on the domain where these patterns were observed.

This work aims to focus on communication app usage specifically during leisure-time and work-time, exploring differences in usage, the development of the frequency of app checking behaviour, and any connection the latter might have with the amount of time spent on the apps.

Based on these reasons, the following research questions and hypotheses arise:

**Leisure-Time RQ: How do users behave with smartphone communication apps in terms of duration and frequency when at leisure?**

- H1: The frequency of communication apps activations varies from day to day during leisure-time.
- H2: Frequency and duration relate with each other, during leisure hours.

**Work-Time RQ: How do users behave with smartphone communication apps in terms of duration and frequency when at work?**

- H3: The frequency of communication apps activations varies from day to day during work-time.
- H4: Frequency and duration relate with each other, during working hours.

CHAPTER 3

# Method

Choosing the appropriate research design method is a crucial step to ensure the defined research questions are answered properly. Following the outlined theoretical findings from Chapter 2, this work uses a quantitative research approach (Creswell, 2009). Furthermore, confirmatory, and exploratory research were considered as the most appropriate methodologies to follow. The reasoning behind this decision lies in the purpose of this work, the literature identified, the method previously used to collect the data and its numeric nature.

Quantitative research is described as the approach of investigating the relationship between variables in a deductive way based on already existing theories (Creswell, 2009). These variables have been collected via instruments and are in a numeric format which allows performing statistical analysis on them. When performing quantitative data analysis, preparing the data, performing descriptive statistics, and choosing the correct inferential statistical tests are an imperative to guarantee reliable results. To ensure this, several quantitative steps were followed (Field, 2009; Sheard, 2018). As a last step, the data was further explored to identify potentially undiscovered relationships by inferential statistics alone. A detailed explanation of the chosen method is presented in this chapter.

## 3.1 Data Collection

The data used in this research was collected by a prior study that made use of an app they had created called YLVI App. The YLVI App-Study was designed and conducted by the Institute of Management Science from the Vienna University of Technology in Austria. The survey period took place from 20.09.2017-11.03.2018. The goal of it was to gather insights on how health, sleep, and work are related to smartphone usage. To achieve this, the YLVI App was developed with the purpose of observing and collecting data about the users' smartphone usage behaviour during work-time, leisure-time, and sleep-time over a period of 14 days. The developed Android app guaranteed an anonymous capturing of the data with solid data security and safety in place.

Overall, there were 237 participants in the study. The country of origin of the participants was 96% from Austria, 2% from Germany, and 2% from other countries. Each of them had to specify their own personal work, leisure and sleep times for each day of the study. These hours varied for each participant and it is interesting to note that the working schedule did not always adhere to the usual 9-17 working hours, but it was more flexible. It encompassed from fixed working hours, flexitime with core time, to shift work. Furthermore, they had to specify the use of their Android smartphone as "private" or "private & professional".

The study employed two data collecting techniques, one in the form of questionnaires which gathered subjective data about the participants' working and health situation, and their point of view on smartphones. Also, daily well-being including the amount of stress perceived on a previous day while at work or at leisure were collected. The perceived stress question was based on a 7-point Likert Scale. The question in original language with the corresponding translation in English can be found in the Appendix A.8. The other technique used was in the form of data logs which recorded what apps were used on the smartphone, the time spent on them, and how often they were activated. At the time of the study, smartphones did not offer the feature of monitoring a user's smartphone activity. Furthermore, the screen time, vibration-, silent-, and flight-mode were tracked. With the collection of these data logs a new research interest arose, particularly to further analyse it with the goal of identifying the users' habit-forming behaviour on communication apps during work-time vs. leisure-time.

## 3.2 Data Description

Not all participants who actively participated in the study fulfilled the criteria for evaluation. Excluded were the ones without recorded data logs, and who worked under one hour per day on average. Also, people not working, and retired persons were not considered.

This resulted in a data set of 75 participants where 40% were female, 57% male, and 3% refused to indicate their gender. The age of the participants ranged between 19 to 65 years (M = 35.20; SD = 25.01). To provide a better overview, the ages were grouped in ranges: 19.48% were up to 30 years old, 28.57% were between 30-40 years old, 28.57% were between 40-50 years old, 19.48% were 50 years old or more, and lastly 3.90% who withheld their age.

Furthermore, 32.74% finished Highschool, 29.87% University or a University of Applied Sciences, 25.97% Teaching, 7.79% Technical or Commercial School, 1.30% Compulsory School, and 2.60% didn't indicate. The job profiles included teacher, graphic designer, nursing assistant, and bike messenger among others. The tenure for these was grouped into categories: 41.89% with up to 5 years tenure, 24.32% between 5-10 years, 20.27% between 10-20 years, 9.46% between 20-30 years, and 9.46% over 30 years tenure.

## 3.3 Data Preparation

The data collected via the YLVI App-Study needed to be cleaned and prepared to be processed and analysed. The starting point was a raw set of log data. It contained the participant ID used for the unique identification of each user, the activity class, and package name for logging the type of activity performed on the app. Also, the app name which captured the app that was accessed, and two timestamps comprised of the date, time and time zone. One timestamp was used to log the starting time of accessing and one to mark the closing of the app. Lastly, some already refined subjective data was also required to create a strong foundation for the data analysis.

### 3.3.1 Data Cleaning

To ensure a thorough data cleaning, the steps outlined in Tobias Geisler Mesevage (2021) were applied on the raw data set by using the tools IBM SPSS Statistics [1] and Microsoft Excel [2].

#### Remove Irrelevant Data

Firstly, as this work focuses on communication apps only, log data that captured the usage of all other apps was removed. Secondly, only those who provided data for a minimum of 10 days were considered as relevant for the goal of this work. This is because a comparable amount of data from each participant is needed to provide accurate results when deriving the user behaviour communication patterns.

Thirdly, the data set contained log data from each participant which we allocated based on subjective data to three different time frames within a day, namely during work-time, leisure-time, and sleep-time. Over the study days when the data was collected, each participant had to fill out a daily questionnaire where they stated which hours belonged to each time frame mentioned before. Important to note is that these domains do not follow a regular pattern, i.e., work-time from 9-17. There were participants who had a regular schedule and others with a more flexible one. In the end, exclusively the data gathered during work-time and leisure-time was kept.

Lastly, for the analysis of the habit-forming user behaviour patterns regarding duration and frequency, solely the participant id, the communication app name, and the starting and ending time of accessing it were retained.

[1] https://www.ibm.com/products/spss-statistics
[2] https://www.microsoft.com/en-us/microsoft-365/excel

### Deduplicate Data

Removing duplicate entries is an essential step to obtain well-balanced results and avoid influencing the analysis. Therefore, the data set was checked for duplicate entries by using the validation feature "Identify Duplicate Cases" from IBM SPSS Statistics and a total of 165 log rows were identified and removed.

### Fix Structural Errors

After taking a deeper look at the remaining data some incongruent naming conventions were identified and fixed as seen in Figure 3.1. This was done to ensure that all data is machine readable, and none left out when performing the analysis.

| From | To |
|---|---|
| Kontakte und WÃƒÂ¤hltasten | Kontakte |
| Telefon ÃƒÂ¢Ã¢â€šÂ¬Ã¢â‚¬Å“ Anrufverwaltung | Telefon |

Figure 3.1: Fixed incongruent namings.

### Deal with Missing Data

A check to single out missing data in all the selected variables was performed, however, none were identified. Hence, there was no need to discard or alter any data.

### Filter out Data Outliers

Another imperative step in the data cleaning process is identifying outliers which can affect the analysis. The challenge of this data set was to differentiate between outliers which can represent long calls made via apps like WhatsApp, goodie call or Viber and those which were just a data logging error (Zach, 2021). Firstly, the data set was sorted descending by the duration of each app usage session - a variable which will be explained in the upcoming subsection - before taking a closer look at the data. Then, some data logging error outliers could be identified. We strongly believe that a call cannot last for 24 hours, nor can one spend 17 hours on the email. Therefore, we decided to remove them. Additionally, we identified a participant who spent an unusual high amount of time on the app goodie call during work-time, affecting the measures of central tendency and spread, hence the participant and their data was deleted from the data set. Apart from these, all data logs were kept, as they can provide insightful information about the users and their communication apps usage behaviour.

## 3.3.2 Data Construction

The next step after data cleaning is data construction. This step is performed when new important attributes need to be derived from the already available ones (Nick Hotz, 2022).

To be able to look at the duration and frequency with which the users access the communication apps the following new attributes had to be derived:

- **Date:** a new variable containing the date in dd-mm-yyyy format of the log data which was derived from the timestamp "start" of the raw data.

- **Start:** is an alteration of the "start" timestamp, modified to mark the start time of accessing a communication app in hh:mm:ss format without including the time zone.

- **Stop:** is an alteration of the "stop" timestamp, fitted to indicate the time of closing the app in hh:mm:ss format not taking the time zone into account.

- **Duration:** represents a new variable, exposing the amount of time in hh:mm:ss format that a user spent on a communication app at a time. It was obtained by performing the function "=MOD([@stop]-[@start];1)" in Microsoft Excel.

- **Slot:** displays a new variable, holding the hour at which an access of an app started, i.e., if a user accesses WhatsApp at 15:01:00 the slot would save 15 as the hour at which the interaction started. This is needed for the mapping of log data to the time frames - work-time or leisure-time - mentioned above. The mapping will be explained at a later stage in this section.

After constructing the new variables which helped performing the data analysis with regard to usage behaviour on duration and frequency, the data set had to be mapped to the two domains this work is focusing on, work-time and leisure-time. For that, the refined subjective data in form of a table were used.

As explained in the previous section, each participant had to fill out a daily questionnaire where they stated what their working and leisure hours were. Based on this information, the mapping of the previously collected data within the YLVI-App Study was performed by using the new variable slot. For each slot it was checked if it belonged to work-time or leisure-time. To capture this information, a new variable called "domain" was created and filled out for each slot with either "WO" for work-time or "LE" for leisure-time. The slots which didn't have any information on the domain were deleted, as they could not provide any valuable information. The split data set can be seen in Figure 3.2.

| participantId | appName | date | start | stop | duration | domain | slot |
|---|---|---|---|---|---|---|---|
| 473-507-221-338 | Outlook | 22.Sep.17 | 07:30:52 | 07:34:14 | 12:03:22 AM | LE | 7 |
| 473-507-221-338 | WhatsApp | 22.Sep.17 | 11:55:16 | 11:57:57 | 12:02:41 AM | WO | 11 |
| 473-507-221-338 | WhatsApp | 20.Sep.17 | 21:51:07 | 21:53:32 | 12:02:25 AM | LE | 21 |
| 473-507-221-338 | Facebook | 21.Sep.17 | 15:41:02 | 15:43:21 | 12:02:19 AM | LE | 15 |
| 473-507-221-338 | Facebook | 20.Sep.17 | 21:17:50 | 21:20:00 | 12:02:10 AM | LE | 21 |
| 473-507-221-338 | Facebook | 21.Sep.17 | 11:24:45 | 11:26:50 | 12:02:05 AM | LE | 11 |
| 473-507-221-338 | WhatsApp | 20.Sep.17 | 21:56:37 | 21:58:42 | 12:02:05 AM | LE | 21 |
| 473-507-221-338 | WhatsApp | 22.Sep.17 | 11:18:37 | 11:20:33 | 12:01:56 AM | WO | 11 |
| 473-507-221-338 | WhatsApp | 22.Sep.17 | 09:41:41 | 09:43:36 | 12:01:55 AM | WO | 9 |
| 473-507-221-338 | WhatsApp | 21.Sep.17 | 20:36:12 | 20:38:01 | 12:01:49 AM | LE | 20 |

Figure 3.2: Data set with added variable domain.

Once the mapping was completed, a further construction step was required before dividing the data set into two files based on the domain. This step included the splitting of those data logs which had a duration stretching over more than one slot. By performing this step, it was ensured that a duration longer than one hour was mapped correctly to its corresponding domain.

However, if the same data set were to be used for descriptive statistics, the accuracy of the results would have been lost as the maximum duration does not exceed one slot, meaning one hour. Therefore, a further step which merged the slots from the same domain into one slot was performed. This guaranteed that i.e., a goodie call of three hours would not be split into three slots of one hour each but remained captured into a single slot as initially collected. Otherwise measures of central tendency like mean and median would have been affected.

Finally, the resulting data set was split into four files which represent the foundation for the data analysis. These are:

1. **Leisure-time:**

   a) LE_Frequency: a data set encompassing the data required for analysing the frequency of accessing the communication apps during leisure-time.

   b) LE_Duration: a data set encompassing the data required for analysing the time spent (duration) on communication apps during leisure-time.

2. **Work-time:**

   a) WO_Frequency: a data set encompassing the data required for analysing the frequency of accessing the communication apps during work-time.

   b) WO_Duration: a data set encompassing the data required for analysing the time spent (duration) on communication apps during work-time.

## 3.4 Descriptive Statistics

After preparing and constructing the data set, the next step is to present these data in another form in order to visualise and portray them better for further analysis. Descriptive Statistics helps with that regard as it acts as "a statistical X-ray" (Riffenburgh & Gillen, 2020) that handles the presentation of data in an apprehensive way (Ibe, 2014).

### 3.4.1 Leisure-time vs. Work-time: Frequency

The results of the measures of central tendency and spread for the frequency are depicted in table 3.1; respectively for work-time and leisure-time.

Comparing the two domains we notice that the mean of frequency per one app session is slightly higher during leisure (36.44 seconds) than work (27.83 seconds). The same is depicted also in the 5% Trimmed Mean that provides a more reliable mean since the standard errors caused by the extreme values (lower and upper end of the population) are reduced. Additionally, when looking the extreme values of frequency, the maximum value of frequency is 621 seconds of one communication app session during leisure-time and 276 seconds of one communication app session during work-time.

**Work-Time vs. Leisure-Time: Frequency Descriptive Statistics**

| | | Work-time | Leisure-time |
|---|---|---|---|
| Mean | | 27.83 | 36.44 |
| Std.Error of Mean | | 1.46 | 1.71 |
| 95% Confidence Interval for Mean | Lower Bound | 24.96 | 33.08 |
| | Upper Bound | 30.7 | 39.8 |
| 5% Trimmed Mean | | 24.18 | 30.46 |
| Median | | 11 | 14 |
| Variance | | 1604.84 | 3494.15 |
| Std. Deviation | | 40.06 | 59.11 |
| Minimum | | 1 | 1 |
| Maximum | | 276 | 621 |
| Range | | 275 | 620 |
| Skewness | | 2.66 | 3.60 |
| Kurtosis | | 8.50 | 18.25 |

Table 3.1: Descriptive Statistics of Frequency during Work-Time vs. Leisure-Time.

On the other hand, the median during leisure-time (14 seconds) is a little higher compared to work-time (11 seconds), but in both domains much lower than the respective means. This shows that there are major outliers in the high end of the distribution and that these are both right-skewed distributions, supported also by the fact that both skewness values are positive. Additionally, by looking at the kurtosis values which are much more larger than 3, it is indicated that these are distributions where most of the values are located in the tails of the distribution instead of around the mean. Regarding the variance, it can be seen that the data is much more spread during leisure-time than in work-time, again because of the much higher maximum value during leisure.

### 3.4.2 Leisure-time vs. Work-time: Duration

Regarding the duration the results of the measures of central tendency and spread for the frequency are summarized in table 3.2; respectively for work-time and leisure-time.

For both domains, almost all the measures are almost the same to one another. The only difference is the maximum of duration, which is 4589 seconds of one communication app session during work-time and significantly higher at leisure-time at 6120 seconds. This fact means that the data is much more spread at leisure-time. The median in both domains is 7 seconds and just like in the case of frequency the fact that it is lower than the mean shows that there are major outliers in the high end of the distribution and that these are both right-skewed distributions. The high value of kurtosis indicates that in these distributions, the majority of the values are located in the tails of the distribution instead of around the mean.

This can be seen as well in the histograms showed in the appendix for work-time A.7 and for leisure-time A.6. What can also observe in the histograms is the fact that a considerable amount of users use their smartphone for a consecutive time of 1 to 10 seconds and another good part up to 150 seconds.

**Work-Time vs. Leisure-Time: Duration Descriptive Statistics**

| | | Work-time | Leisure-time |
|---|---|---|---|
| Mean | | 35.39 | 35.00 |
| Std.Error of Mean | | 0.81 | 0.57 |
| 95% Confidence Interval for Mean | Lower Bound | 33.79 | 33.87 |
| | Upper Bound | 36.99 | 36.12 |
| 5% Trimmed Mean | | 21.29 | 20.87 |
| Median | | 7 | 7 |
| Variance | | 12363.48 | 12649.40 |
| Std. Deviation | | 111.19 | 112.46 |
| Minimum | | 1 | 1 |
| Maximum | | 4589 | 6120 |
| Range | | 4588 | 6199 |
| Skewness | | 18,173 | 19.58 |
| Kurtosis | | 553.21 | 690.93 |

Table 3.2: Descriptive Statistics of Duration during Work-Time vs. Leisure-Time.

## 3.5 Hypotheses Testing

The goal of this chapter is to test our hypotheses from 2.5 and determine the validity of our claims based on the dataset. To do this, we will perform hypotheses testing on the non-parametric dataset we have in order to make inferences about the users and make statistical decisions.

For both variables, duration and frequency, there is a non-normal distribution and additionally the skewness and kurtosis are very high in both. For these reasons the Hypotheses Tests that can be used are non-parametric tests, such as the Spearman Rank Correlation Test and the Augmented Dickey–Fuller Test, instead of the more commonly used parametric tests.

SPSS [3] is used for conducting non-parametric tests, including Spearman Rank Correlation, due to its user-friendly interface and statistical capabilities. On the other hand, R was used for Time Series Analysis due to its built-in functionality and ease of use for this type of analysis.

#### Time Series Analysis

With the first and third hypothesis we want to test if the frequency at which users access smartphone communications apps during work-time and leisure-time varies from day to day during the time-frame that the data was collected. As the data was gathered over a set period of time and on a consistent basis, a time series analysis is appropriate to use for testing.

Time series analysis is a method that looks at a series of data points which were gathered over a set time course and collected on a regular basis. It is a unique form of data analysis as it allows to understand how variables change over time, with time being a crucial variable. To achieve reliable results, a large number of data points are required to cut through noisy data and account for seasonal variance. The consistency and representative sample size of the data set ensures that any trends or patterns discovered are not outliers. In our particular case we want to test if the time series is stationary. A time series is said to be stationary when the following conditions are met: the mean of the time series is constant over time, variance does not rise over time, and seasonal effects are minimal.

For the purpose of testing the time series of the frequency of communication apps activations with regard to both domains, the Augmented Dickey-Fuller Test (ADF Test) was chosen. The ADF Test is a statistical method used to test the null hypothesis that a time series is non-stationary based on its unit root characteristic[4]. In the context of our hypotheses, this test can be used to assess if the frequency of app activations varies from day to day throughout the given time.

[3]Statistical Product and Service Solutions
SPSS is a widely used statistical software provided by IBM that provides various statistical techniques and tools for data analysis. https://www.ibm.com/spss

[4]Unit root is the characteristic which decides if a time series is stationary or not.

In our case, the ADF Test is applied on the time series of communications apps activations of each participant resulting into 75 time series in the end. Therefore, as a last step before interpreting the result, it is needed to apply a Bonferroni Correction Test. This looks at hypothesis tests with multiple comparisons, in our case 75, and minimizes the appearance of a false positive. Once this is conducted, we can ensure that our data will not show incorrect statistical significance and we can rely on the result obtained by the ADF Test.

The above presented hypotheses testing approach was defined and performed with the support of Dr. Alejandra Avalos-Pacheco[5], who is an University Assistant at Vienna University of Technology in Vienna, Austria.

**Spearman‘s Correlation Coefficient**

The second and fourth hypothesis of this work aim to test if the duration and frequency of communication apps correlate or not with each other during work-time and leisure-time.

Spearman‘s Correlation Coefficient is a statistical test used to determine the strength and direction of the relationship between two variables. To compute the Spearman’s Correlation Coefficient, first, the values of each variable are ranked from lowest to highest. After that, the difference between the ranks is calculated. The correlation coefficient between duration and frequency is an important indicator of the relationship between these two variables. A coefficient of +1 indicates a perfect positive correlation, while a coefficient of -1 indicates a perfect negative correlation. On the other hand, a coefficient of 0 means that there is no correlation at all between the two variables.

In the context of our hypothesis testing approach, we use the Spearman’s Correlation Coefficient to test if the variables, duration and frequency, have a correlation with each other during work-time and leisure-time. By calculating the coefficient, we can determine if an increase or decrease in duration is associated with a corresponding increase or decrease in frequency. This can help us to identify patterns or relationships between the two variables and can be useful in deriving users’ behaviour with communication apps within the two domains.

To perform the test, the coefficient was calculated using the SPSS tool. The resulting coefficient will then be used to interpret the relationship between the two variables and make inferences about their association.

[5] Dr. Alejandra Avalos-Pacheco’s Website

### 3.5.1 Leisure-time Domain Analysis

In this sub-chapter, the research question of the leisure-time domain as well as the relevant and corresponding hypotheses will be tested using the non-parametric tests previously discussed in this chapter.

**RQ: How do users behave with smartphone communication apps in terms of duration and frequency when at leisure?**

- H1: The frequency of communication apps activations varies from day to day during leisure-time.
- H2: Frequency and duration relate with each other, during leisure hours.

In the proceeding sections, each of the hypothesis will be taken separately and discussed with regard to the statistical methods that were used to test each one of them. By analysing the data using these statistical methods, we will be able to gain a better understanding of the relationships between the distinct variables in question - duration and frequency - as well as the factors that influence individuals' leisure-time behaviour with regard to communication apps usage.

#### Hypothesis 1

In this section, we will discuss the findings of our study on the hypothesis that the frequency of communication apps activations varies from day to day throughout the leisure-time. In order to find out, we conducted a Time Series Analysis using the Augmented Dickey-Fuller (ADF) Test on the time series of communication app activations for all participants. For a thorough explanation of the steps followed to test, see the Appendix A.2.

**ADF Test** - We first converted the data set in a time series object and then applied the ADF Test to each time series. This means that each time series is tested independently and that the time series was tested as a whole - not comparing each value of a time series to the next one. The ADF Tests if the data is non-stationary (meaning means, variances, and co-variances that change over time) or if the data is stationary.

**Bonferroni Correction** - Since we had to do the test for each participant, we performed a Bonferroni Correction to the ADF Test results in order to minimize the likelihood of having false positives and to adjust the significance level to account for multiple comparisons.

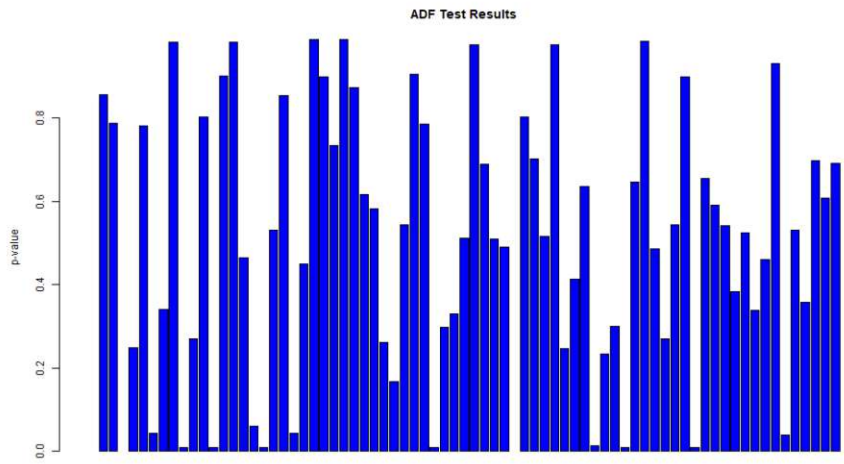



Figure 3.3: Leisure-time H1: Augmented Dickey-Fuller Tests on the data set.

The ADF Test results (see A.2) showed that none of the p-values were smaller than our significance level of alpha=0.05/75 - meaning that the data is non-stationary and that it varies from day to day throughout the leisure-time. The plot of the p-values can be observed in 3.3 - showing the p-values obtained for a for each test, which are greater than 0.05/75 suggesting that we cannot reject the hypothesis and that the time series is likely non-stationary. These findings imply that **Hypothesis 1 is supported** ⇒ the frequency of communication apps activations varies from day to day during leisure-time.

### Hypothesis 2

In this section, we investigate the relationship between the variables of frequency and duration in the context of communication apps usage during leisure-time. The hypothesis we explore is that there is a relation between the two aforementioned variables, regardless of whether the usage occurs in different parts of the leisure-time. To test this hypothesis, we went on to use the Spearman's Correlation Coefficient, a statistical method that measures the strength and direction of the relationship between two variables.

In our study, the Spearman's Correlation Coefficient between duration and frequency variables during leisure-time is 0.73. This indicates that there is a strong positive correlation between the two variables. The significance level of 0.01 indicates that the probability of observing such a correlation coefficient due to chance is less than 1%. This is a strong indication that the correlation between duration and frequency is not due to random chance, but rather reflects a real relationship between the two variables.

Using a scatter plot graph (see Figure 3.4), we can further support the relation of the two variables that the Spearman's Correlation Coefficient test already supports. The scatter plot in our research illustrates the correlation between the two variables, duration of communication apps usage and frequency of communication apps activations.

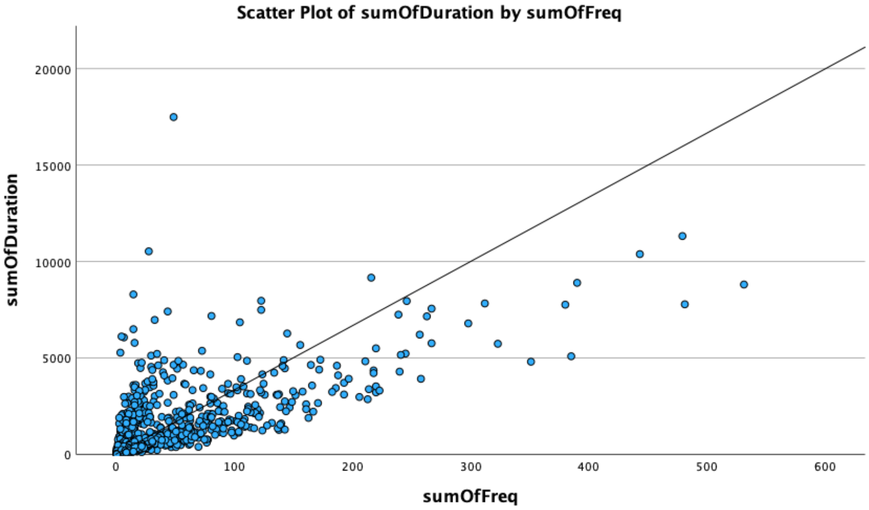
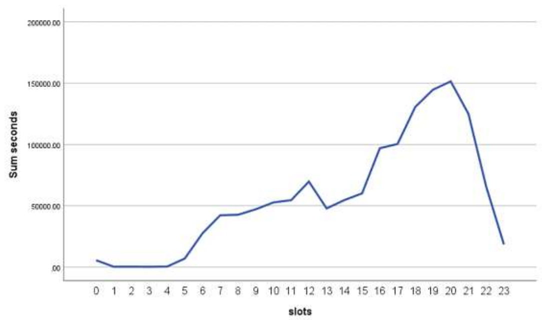
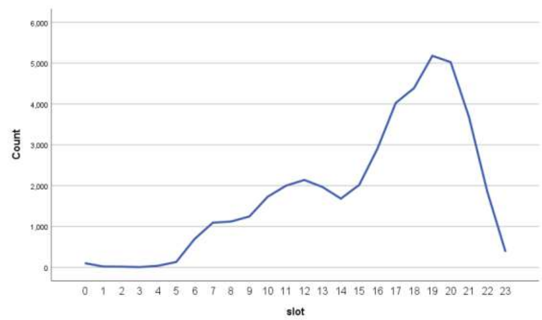



Figure 3.4: Leisure-Time H2: Scatter Plot of sumOfDuration by sumOfFreq.

The scatter plot's dots can be seen to be relatively close to the line, displaying a significant positive association between both variables - duration and frequency - just like the test results showed. The few outliers scattered around the line can be attributed to individual differences in communication app usage patterns that do not follow the trend of the general population - keeping in line with the correlation coefficient not being a perfect positive correlation (+1) but still being a strong positive correlation (+0.73).




(a) Duration per Slot




(b) Frequency per Slot

Figure 3.5: Leisure-Time H2: Duration and Frequency per Slot.

Furthermore, the study used line graphs to help illustrate the findings of the Spearman's Correlation Coefficient test - depicted in Figure 3.5. These line graphs show the relationship between the variables of duration and frequency with the slot of the day in which they occurred. By looking at the graphs, it becomes easier to see how the two variables are related and how they change over the course of the day during leisure-time. The lines in both graphs have a similar shape and spike at almost exactly the same slots of the leisure-time. This indicates a relation between duration of use and frequency of communication app activations and the time of day when they occur. Consequently, we can say that **Hypothesis 2 is supported** ⇒ the frequency and duration relate with each other, during leisure-time.

### 3.5.2 Work-time Domain Analysis

This section presents the analysis results obtained from testing the hypotheses derived from literature regarding the research question that focuses on the work-time domain. The findings of each hypothesis will be presented and discussed to highlight how the work-time domain affects the user behaviour of smartphone communication apps usage.

**RQ: How do users behave with smartphone communication apps in terms of duration and frequency when at work?**

- H3: The frequency of communication apps activations varies from day to day during work-time.
- H4: Frequency and duration relate with each other, during of working hours.

#### Hypothesis 3

The third hypothesis focuses on the variable that holds the frequency at which the users check the communication apps during work-time. As presented in section 3.2, the data was logged over a given period of a minimum of ten days, time being here a critical factor in identifying a pattern for the frequency of use. Because of this, the fitting test was a time series analysis, respectively the ADF Test which tests for stationarity.

The data set tested contains the summed-up accesses of each user per hour during work-time, however stretching over a full day (24 hours) because of different employment types. Once these data set was prepared, the ADF Test was performed in the R tool. Figure 3.6 shows the results of the tests in plots, where each bar counts for the behaviour of one user.

As it can be easily noticed, the results from user to user vary a lot, hence the bars that make up for a dynamic behaviour overall during work-time. However, before being able to draw a conclusion we needed to apply a Bonferroni Correction to the ADF Test results. This is because multiple tests were employed, specifically 75 in our case, as we have 75 participants. By applying the correction, we minimized the chances of a Type I error which could have led to falsely rejecting the null hypothesis. Nevertheless, the p-value of the result is $> 0.05$ which means the alternative hypothesis is rejected and the null hypothesis of non-stationarity is supported. To conclude, **the hypothesis is retained** ⇒ the frequency of communication apps activations varies from day to day during work-time. A detailed look at the steps performed in R can be found in the Appendix A.3.

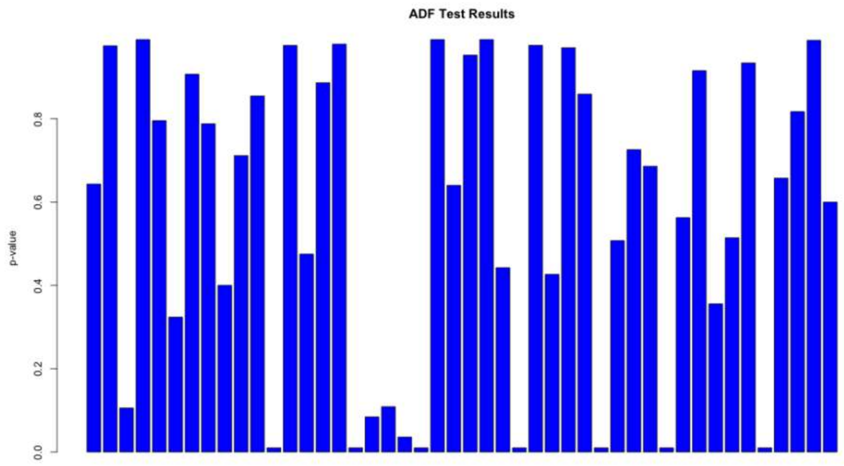



Figure 3.6: Work-time H3: Augmented Dickey-Fuller Test on the data set.

### Hypothesis 4

The fourth hypothesis in the context of the work-time domain aims to find out if a relationship between the two variables - duration and frequency - can be established during working hours. In order find out, we tested for correlation. Since the data we have is non-parametric, Spearman's Correlation Coefficient was used.

The behaviour of our participants revealed a correlation coefficient of 0.707 which is significant at the alpha level of 0.01. This indicates a medium to strong relationship moving towards 1 (perfect positive correlation), hence evidence that a mutual connection between duration and frequency exists. This is reinforced by the significance level of 0.01 which means that 99% percent of the observations did not happen randomly.

Figure 3.7 shows a visual graph in form of a scatter plot which draws the correlation between the observed points. Apart from some outliers, it can be noticed how most points are forming a composite around duration = 4000 seconds and frequency = 100 checks.

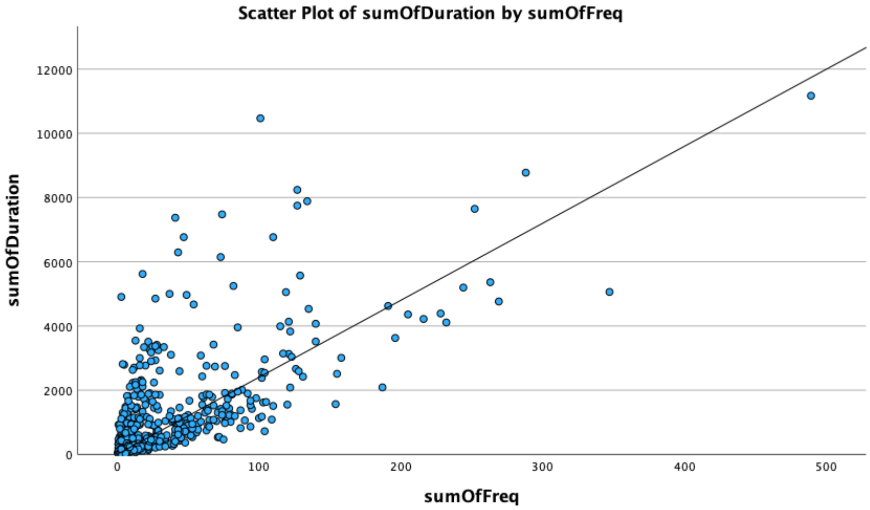
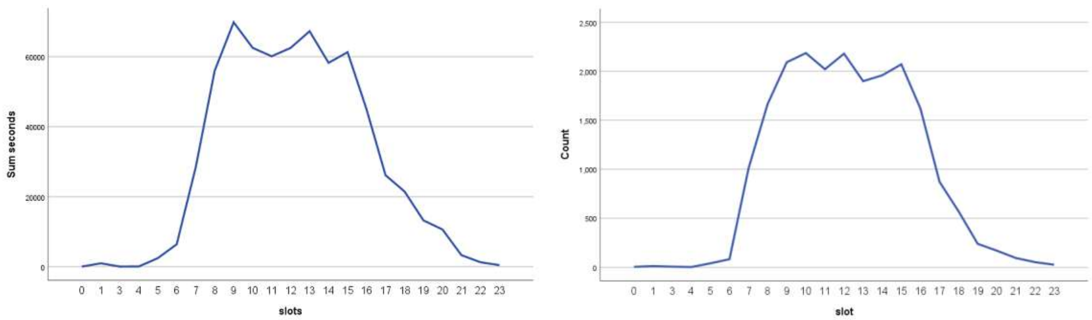



Figure 3.7: Work-Time H4: Scatter Plot of sumOfDuration by sumOfFreq.

Furthermore, by comparing duration and frequency per slot in form of a line graph as it can be seen in Figure 3.8 we can observe how both variables grow in tandem until they reach the highest values around midday. Once the afternoon starts, an abrupt and simultaneous decrease in both the time spent and frequency of checking the communication apps can be noticed with a slower tendency once the evening approaches.




(a) Duration per Slot

(b) Frequency per Slot

Figure 3.8: Work-Time H4: Duration and Frequency per Slot.

To conclude, the results obtained from our test support the hypothesis, therefore **the hypothesis is retained** ⇒ frequency and duration relate with each other, during working hours.

## 3.6 Exploratory Analysis

The objective of this section was to explore the leisure-time and work-time domain with regard to communication apps usage in order to understand the usage patterns employed by users. After finding support for our hypotheses which state that duration and frequency relate with each other during leisure and working hours, we decided to explore in detail the two measurement variables by including additional ones like the communication apps and the smartphone usage type to derive communication patterns for both domains. The target was to better understand the users' overall behaviour with regard to communication app usage per day, but also the differences between weekdays and weekends. This is because not all participants follow a traditional work arrangement, therefore a distinctive behaviour might be followed based on the day of the week.

Additionally, we also looked at the engagements per communication app with the aim of determining if a change in behaviour can be observed from one communication app to the other. Lastly, we took a closer look at users' behaviour based on the smartphone usage purpose. As already stated before in Section 3.1, it was intended either for private usage only or for both private and professional use. This would provide us insight into potential blurred boundaries between the two domains if the communication apps were used for work-related purposes during leisure-time or non-work-related activities during work-time, indicating a cyberslacking behaviour.

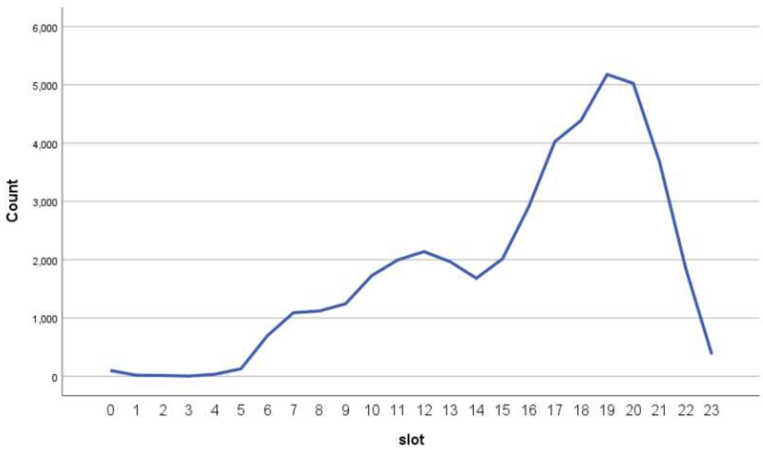
For the analysis we employed descriptive statistics and visualization techniques. In addition, to identify groups of users, the Two-Step Cluster Analysis was used. The reasons behind lie in the accuracy of results it provides, the fact that it can handle mixed data types, and is considered more objective than other traditional clustering methods (Kent et al., 2014). Lastly, the levels of perceived stress within the identified groups were computed based on the users' self-reported data. The responses followed a 7-point Likert Scale and the question with its corresponding answer options can be found in the Appendix A.8.

### 3.6.1 Leisure-time Domain

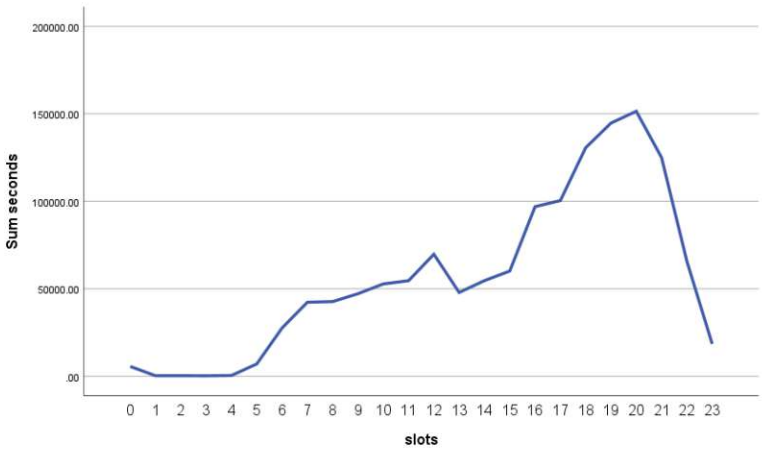
#### Smartphone Communication App Usage per Day

The first set of graphs in Figure 3.9 display the relationship between duration and frequency of usage per time of day. The graphs show that duration and frequency of app usage are closely related, with both peaking at the same times. The peaks occur around 11-13 o'clock and 19-21 o'clock.

The results indicate that when users use smartphone communication apps more frequently, they prefer to use them for a longer period of time. The peaks at 11-13 o'clock and 19-21 o'clock suggest that these times are popular for leisure-time app usage, possibly indicating a pattern of using the apps during breaks at work or after work hours - especially before sleeping. Additionally, the close relationship between duration and frequency of app usage per time of day may also suggest that users tend to use these apps for a longer duration during their free time or leisure-time. An argument backing up this finding could be because during these periods, users have more time to spend with these apps as part of their leisure activities.




(a) Leisure-time: Frequency




(b) Leisure-time: Duration

Figure 3.9: Leisure-time: Duration vs. Frequency per Slot Chart.

The results indicate that when users use smartphone communication apps more frequently, they prefer to use them for a longer period of time. The peaks at 11-13 o'clock and 19-21 o'clock suggest that these times are popular for leisure-time app usage, possibly indicating a pattern of using the apps during breaks at work or after work hours - especially before sleeping. Additionally, the close relationship between duration and frequency of app usage per time of day may also suggest that users tend to use these apps for a longer duration during their free time or leisure-time. An argument backing up this finding could be because during these periods, users have more time to spend with these apps as part of their leisure activities.

Further analysis of the data reveals that during the 11-13 o'clock time frame, users tend to use smartphone communication apps such as Facebook, WhatsApp, Email, and Contacts the most. This could suggest that users are more likely to use these apps during work breaks or when catching up with friends and family during lunchtime. On the other hand, during the 19-21 o'clock time frame, the most popular communication apps include Facebook, Instagram, WhatsApp, Snapchat, Twitter, and Telegram. This finding could suggest that users are more likely to use these apps during their leisure-time or after work hours when they have more free time to engage with social media and interact with their friends and followers. These apps may provide users with a form of entertainment and a way to stay connected with others during their free time.

In addition to the relationship between duration and frequency of smartphone app usage, other statistical measures were collected to better understand users' behaviours. The data shows that on average, users spend approximately 26 minutes per day using smartphone communication apps during leisure-time. This average time spent using apps is relatively the same across all days of the week, including weekdays and weekends - as there is not a significant change between the two. The maximum duration of app usage was found to be 4.8 hours, indicating that some users engage in extended usage of these apps and may indicate a possible addiction to these apps.

In terms of frequency of smartphone app usage, the data shows that on average, users check their phones approximately 49 times per day. Similar to the duration of app usage, this average frequency stays relatively the same across all days of the week. However, the maximum frequency of app usage was found to be 676 checks, indicating that some users have a much higher tendency to briefly check these apps more frequently throughout the day.

As part of the exploratory analysis of duration during leisure-time we also built histograms which reveal interesting patterns, depicted in the appendix A.6. The histograms are divided into five intervals: "Up to 1h", "Up to 30min", "Up to 15min", "Up to 5min", and "Up to 1min". The majority of app usage sessions falls within the intervals of "Up to 1min" and "Up to 5min", indicating that users tend to spend their time on the phone with frequent sequences of short duration. This suggests that users engage in quick interactions or communication, possibly checking notifications or responding to messages in brief bursts of app usage. The data supports the argument that users prefer frequent, short sessions of app usage during leisure-time, aligning with the earlier findings of the state-of-the-art on app checking frequency.

Overall, these statistical measures provide insight into users' behaviours and patterns when it comes to smartphone communication apps. The findings suggest that the duration and frequency of smartphone communication app usage are closely related and tend to peak at specific times of the day. These patterns could be indicative of specific user behaviours and preferences, which could be further investigated in future studies.

### Smartphone Communication App Usage per Communication App

To understand the usage pattern of communication apps, a bar chart was created to depict apps based on the duration and frequency of usage during leisure-time - see Figure 3.10.

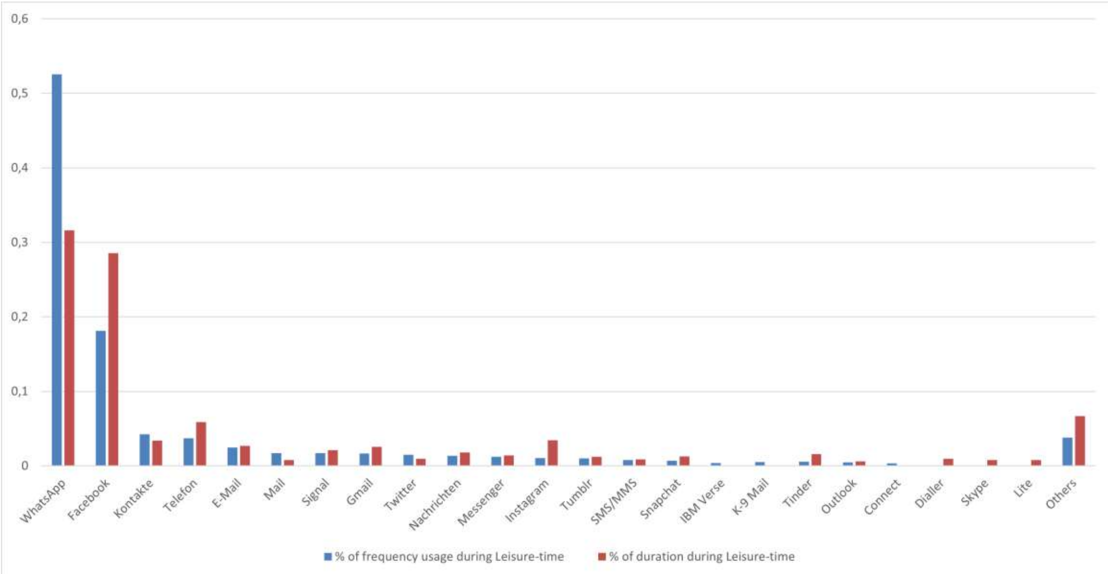



Figure 3.10: Leisure-time: Duration and Frequency per Communication App.

In the Figure interesting patterns can be observed in terms of frequency and duration of app usage. Among the communication apps, WhatsApp and Facebook, along with email and contacts apps, were found to have the highest frequency and duration of usage. Interestingly, WhatsApp and Facebook have almost the same percentage of duration overall, but WhatsApp has double the frequency of checks. While the mailing apps take a considerate number of minutes and checks during leisure hours, we cannot assume if that was for work or personal use. To be noted is also the fact that IBM Verse has a fair number of app checks during the leisure hours, indicating that participants were for sure checking their work emails, as this mailing app is used by companies only.

On the other hand, Instagram showed a high duration of usage but not as high frequency, indicating that users tend to spend longer periods of time on Instagram, possibly browsing through photos and engaging with content, but with lower frequency compared to Facebook and WhatsApp. Furthermore, the analysis also revealed that the majority of the communication apps - shown as "Others" - were used for a short duration of time and infrequently during leisure hours. This suggests that these apps may not be as engaging or frequently used by users during their leisure-time.

Furthermore, for each participant, we determined the top app used and found that WhatsApp was the most used app by females in their 40s while Facebook was the most used app by mostly males in their 30s. Telefon was the top app used by mostly males in their 30s, while Kontakte was the most used one by males in their 30s. Lastly, Connect was the most used app by males over the age of 50.

In addition to calculating the top apps used by each participant, we also examined the most frequently checked apps across all participants. Facebook was the most frequently checked app for mostly females in their 30s, while WhatsApp for males in their 40s. To be noted, there was a group of users who showed a higher frequency of WhatsApp checking and the difference to the latter group mentioned is that these users were males in their 30s.

These findings provide insights into the usage patterns of different age and gender groups, highlighting the popularity of certain communication apps among specific demographics.

### Clustering per Smartphone Usage Purpose

Lastly, we aimed at classifying users into different groups based on their behaviour. For this purpose, we employed three factors: how long and how often the individuals used their phone, and whether they used a phone for both personal and professional purposes (Dual Purpose) or solely for personal use (Private Purpose). During leisure-time three groups were identified.

Out of all the participants examined during leisure-hours, roughly 53% belonged to the *Private Purpose Users* group. Most of them were males in their thirties and forties. The communication apps that these users would spend most of their time were mainly WhatsApp and Facebook, with slightly less usage of Kontakte, Signal, and Telefon. The apps they checked most often were WhatsApp and Facebook, but this time WhatsApp was significantly more frequently checked than the other communication apps.

Furthermore, 40% of the participants belonged to the *Dual Purpose Users* group. Most of them were men in their twenties. Their preferred and most frequently checked apps were again WhatsApp and Facebook, along with a few other apps in small proportions. However, the difference between the usage and checking of these two apps wasn't significant.

Approximately 7% of the participants displayed excessive phone usage while using their phone in both modes and thus were grouped to the *Dual Purpose Excessive Users* cluster. In contrast to the other two groups, the majority were women in their thirties. The most used apps in this group were only WhatsApp and Facebook, with WhatsApp being the most frequently checked app among all the users in this cluster.

Across all three groups, users generally had a tenure of up to 5 years. What's noteworthy is that the mean frequency and duration of phone usage in the *Private Purpose Users* and *Dual Purpose Users* clusters are relatively similar, with slightly higher figures in the *Private Purpose Users*. Specifically, the mean frequency was 557 and the mean duration was 4.64 hours in the *Private Purpose*, while the mean frequency was 536 and the mean duration was 4.35 hours in the *Dual Purpose Users* group. However, the *Dual Purpose Excessive Users* group has a much higher mean frequency of 3709 and duration of mean 9.84 hours. This indicates that during leisure-time an excessive usage is possibly connected to work related tasks since the smartphones are in the dual purpose mode.

According to the stress levels reported by participants, it appears that all three groups experienced relatively low levels of stress. The *Private Purpose Users* group had the lowest reported stress level with an average score of 2 out of 7. The *Dual Purpose Users* group reported a slightly higher stress level with an average score of 1.90 out of 7. The *Dual Purpose Excessive Users* group had the highest stress level among the three groups with an average score of 2.60 out of 7. It is interesting to note that even though the *Dual Purpose Excessive Users* group had the highest stress level, the difference in stress levels between the three groups is relatively small. This suggests that smartphone usage may not be a significant source of stress for these participants. However, it is important to note that this study only measured self-reported stress levels, and other sources of stress in participants' lives may have influenced these results.

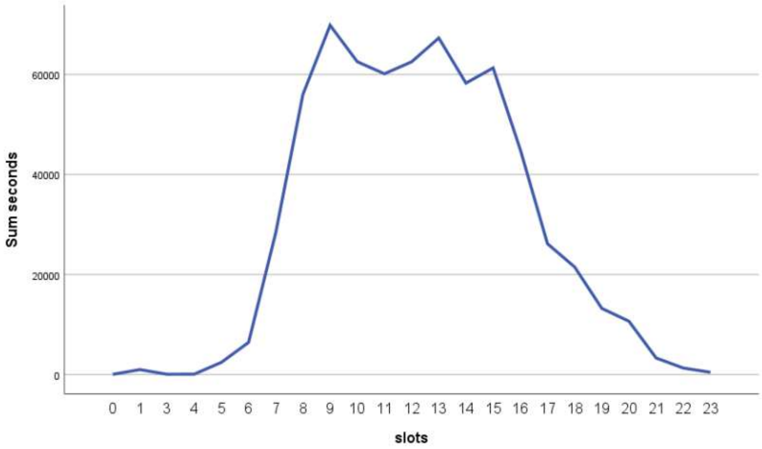
### 3.6.2 Work-time Domain

#### Smartphone Communication App Usage per Day

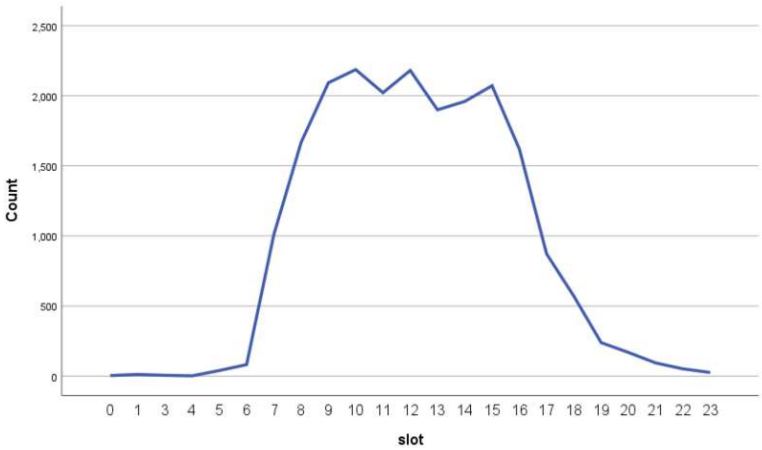
To determine the communication app usage in terms of duration and frequency per day we have computed them based on slots where one slot represents one hour of the day. Figure 3.11 depicts the obtained results. During work-time, over the whole study period, it can be noticed that participants spend the most time on communication apps between 8-9 o'clock, 12-13 o'clock, and around 15 o'clock. Similarly, for the communication app checking frequency, the peaks were identified at 10 o'clock, 12 o'clock, and 15 o'clock. Once again, this reinforces the close relationship between duration and frequency that supported our hypothesis. It indicates that the moment a user checks on their smartphone they also engage for a longer period with the received notifications.

When looking at the time of the day these are happening, we can observe that the first peak is in the morning when a regular working day would start. This could implicate that users could be checking on their latest work updates but also that they might allocate more time to communicate with their work colleagues or family and friends, as well as reading the latest news of the days before delving into work responsibilities. The preferred apps are Facebook and WhatsApp, along with the in-built smartphone apps for text-messaging and calling.

However, curious to see is the difference between the first peak of duration and frequency which happens one hour later. It is indicative that after spending time on the communication apps users put their smartphone away to start working but they might receive many notifications afterwards for which they don't take the time to engage with but rather just briefly check on them. The second peak for both duration and frequency hints at the lunch break where users not only check the received notifications from their last check but also have time to interact with them and reply.




(a) Work-time: Duration




(b) Work-time: Frequency

Figure 3.11: Work-time: Duration vs. Frequency per Slot Chart.

The most used apps around this time are again Facebook, WhatsApp, and calling with the addition of Instagram and E-Mail. Lastly, the peak at 15 o'clock could indicate one last short break before a regular working day would be concluded with users engaging apart from the before mentioned apps also with Snapchat, Tinder, Twitter, and Tumbler. From the types of apps alone we can already identify a cyberslacking behaviour which seems to appear towards the end of the working day when users might already be tired and losing focus.

To find out the duration and frequency of communication apps usage during work-time, we have calculated the measure of central tendency. Users spend on average 20 minutes per day during work-time on communication apps alone whereas during weekends also during work-time, it drops to 19 minutes. The difference is too small to be able to draw any conclusions from it.

Nevertheless, important to note is that this duration makes up only communication apps to which the duration of all other app categories would have to be added to come to the total usage during work-time. For the frequency of use during work-time, we determined that users engage on average in 35 checks during weekdays, and only 30 checks during weekends. Since both measurements represent a behaviour during work-time, it is difficult to draw a conclusion on why the frequency is dropping considerably. On one hand, an argument could be the smaller sample size of the study participants who worked during weekends, on the other hand it could also imply that less notifications were received as other work colleagues, or friends and family might be less active on their smartphones during weekends due to other leisure activities. Furthermore, the maximum values for duration and frequency were identified at 3.10 hours respectively 527 checks per day depicting an excessive behaviour during work-time.

Lastly, we have grouped the app sessions to determine users' most common behaviour in terms of duration and frequency. The results presented in A.7 show that users prefer short app sessions of up to one minute, and up to five minutes. This implies that during work-time users would rather briefly check the communication apps without spending too much time with them rather than engaging in long interactions.

#### Smartphone Communication App Usage per Communication App

With the purpose of better understanding users' engaging behaviour with communication apps during work-time, we analysed the distribution of duration and frequency per app. As it can be seen in Figure 3.12, WhatsApp and Facebook are the two top apps regarding both duration and frequency of use. These are followed by the in-built apps of each smartphone used for calling and text-messaging. Lastly, the last pair of apps which receive considerate attention during work-time are E-Mail provider apps.

If we compare WhatsApp with Facebook, what can be noted is that although WhatsApp accounts for a higher frequency, the time spent on the app is lower compared to Facebook which depicts a lower frequency. This could be explained by the variety in offering of these apps. WhatsApp provides users with the possibility of communicating with their contacts in form of messages, voice messages and calls, and video calls. The high frequency of our participants could indicate that they communicate asynchronous over WhatsApp by exchanging information in short sessions with their contacts which would account for a higher checking behaviour. Facebook, in addition to that, offers news, a marketplace, groups on different topics, as well as the possibility to post pictures, videos, and status updates. These are naturally more engaging and can immerse the user in a scrolling behaviour that consequently leads to spending more time on the app. The high users of WhatsApp both in terms of duration and frequency are females in their 30s and

40s while males up to 30s opt for Facebook.

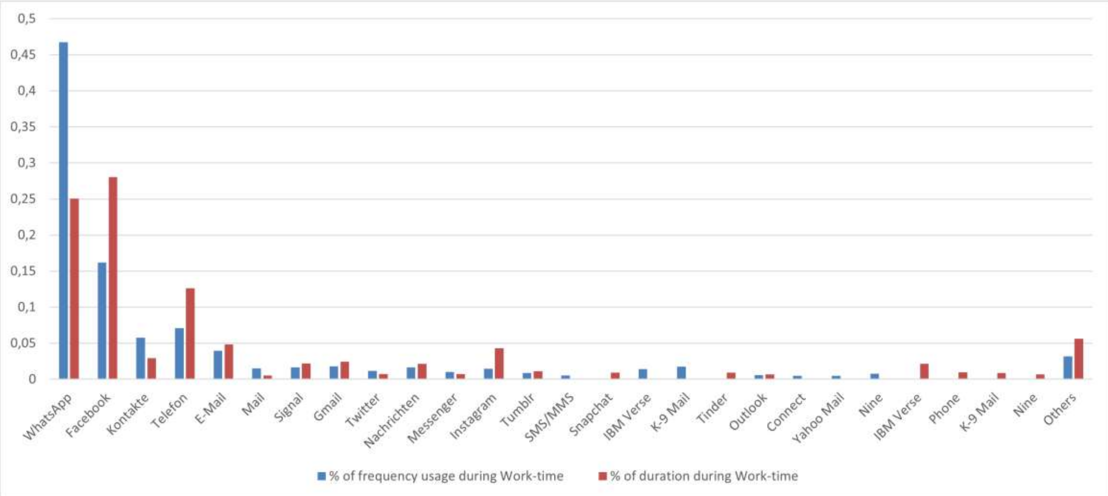



Figure 3.12: Work-time: Duration and Frequency per Communication App.

The in-built apps for calling and text-messaging like Kontakte and Telefon depict a lower usage. Telefon scores higher for duration compared to its frequency while Kontakte is preferred for checking rather than engaging sessions. One potential argument is the design of these apps. While Kontakte is destined to search for a contact and its details, Telefon's purpose is to make calls which would lead to a higher duration as identified in this case. Males in their 30s opt for making calls via Telefon while the ones up to 30s and over 50s prefer to access Kontakte.

The E-Mail provider apps score similarly in both duration and frequency, pointing out that once a user accesses the app, they also take the time to read their inbox, write an email or reply to it. Lastly, apps like Twitter, Instagram, Snapchat or Tinder are also among the more frequent used apps during work-time whereas the group of apps marked with Others have a very low and infrequent use, and therefore do not appear in the bar chart.

### Clustering per Smartphone Usage Purpose

As a last step in our exploratory analysis, we decided to identify groups of users based on their behaviour with regard to frequency of checking, duration of use, and smartphone usage type - private (Private Purpose) or both private and professional (Dual Purpose) during work-time. We were interested in this behaviour foremost out of the reason that it might be indicative of cyberslacking behaviour. The clustering resulted in three groups of users.

The *Dual Purpose Users* cluster is comprised of those who used their smartphone for both private and professional use and accounts for 42.70% of the participants. It is constituted out of males in their 30s and 40s in proportion of 60%. Their preferred communication app both in terms of duration and frequency is WhatsApp. The mean duration of use over the period of the study was 2.64 hours whereas the frequency 470 checks. Taking into consideration that the smartphone is intended for work purposes as well and WhatsApp offers WhatsApp for Business, an enhanced version of the regular app, which is dedicated for business use, it is inconclusive if the behaviour during work-time could be categorized as cyberslacking activity.

The *Private Purpose Users* cluster is covered by those who used their smartphones for private purpose only and accounts for 52% of the users. It is comprised of males in their 30s and 40s in proportion of 60%. WhatsApp was once again the top used app both in terms of duration and frequency. The mean duration of use over the period of the study was 1.64 hours whereas the frequency 294 checks. However, in this case, it could be determined that participants within this group were engaging in non-work activities during work-time, therefore they could be categorized as users who engage in cyberslacking behaviour.

The *Private Purpose Excessive Users*, as a last cluster, is constituted out of those participants who used their smartphone for private purposes during work-time as well but were categorized as high users due to an extreme behaviour. This group accounts for 5.30% out of all participants and was comprised of females in their 30s and 40s in proportion of 75%. Interestingly, WhatsApp and Facebook share an equal proportion of 50% both in terms of duration and frequency. The excessive use is confirmed by the average duration of 6.90 hours of use and average frequency of 4952 checks over the period of the study. This demonstrates an extreme cyberslacking behaviour which could not only highly impact the job performance but also pose serious concern about the users' stress levels and overall well-being.

The amount of stress perceived by users during work-time was also recorded at the time of the YLVI App-Study. These were computed for the three clusters and the results are similar. The *Dual Purpose Users* experienced on average stress of 3.12 out of 7, the *Private Purpose Users* 3.19 out of 7, and the *Private Purpose Excessive Users* 3.25 out of 7. This indicates that all groups had a rather neutral attitude towards the perceived stress at work, nevertheless, what can be noticed is that with the increase of private smartphone usage during work-time, the mean score rises. In conclusion, although a rise can be noted, no information about what exactly caused users to perceive stress at work is available, hence no relation between an increased private smartphone usage and level of stress can be made.

### 3.6.3 Analysis of Leisure-time vs. Work-time

#### Smartphone Communication App Usage in Terms of Frequency

In Figure 3.13, the total amount of communication apps checks for all participants has been spread over 24 hours (slots) in a multiple-line chart (a blue line for leisure-time and red line for work-time).

The graph depicting the frequency of communication apps checking during the day reveals interesting patterns in relation to leisure-time and work-time. From the morning hours until around 15 o'clock, the frequency of app checking appears to be similar for both leisure-time and work-time, with a slightly higher frequency observed during work-time. This could be attributed to the fact that during work hours, individuals may need to check their communication apps more frequently for work-related purposes, such as responding to emails or messages from colleagues or clients.

However, the graph shows a notable shift in the pattern after 15 o'clock, with the frequency of communication apps checking during leisure-time almost doubling and reaching its peak at 20 o'clock. This suggests that during leisure-time, particularly in the evening hours, users tend to check their communication apps more frequently compared to work-time.

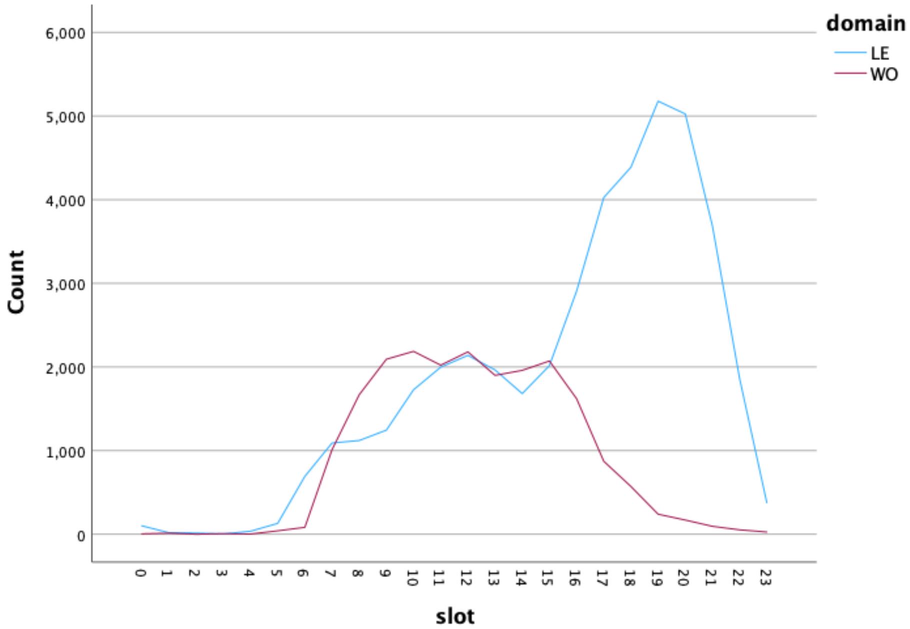



Figure 3.13: Leisure-time vs. Work-time: Frequency per Slot Chart.

To better visualize the most frequently checked communication apps there are the bar charts in figure 3.14. The chart depicts the fact that in both domains WhatsApp and Facebook hold the greater part of app-checking - both apps with higher frequencies during leisure-time. Throughout work-time, there seems to be frequent checks of communication apps that can be used for work purposes as well, such as mail, call and messaging services. Whereas, while at leisure-time, there are social media apps that score higher, for instance Snapchat, Twitter, Tumblr, Instagram, Messenger, and Signal. To be noted, is the fact that also while outside of working hours there is still a considerable number of checks for the mailing apps.

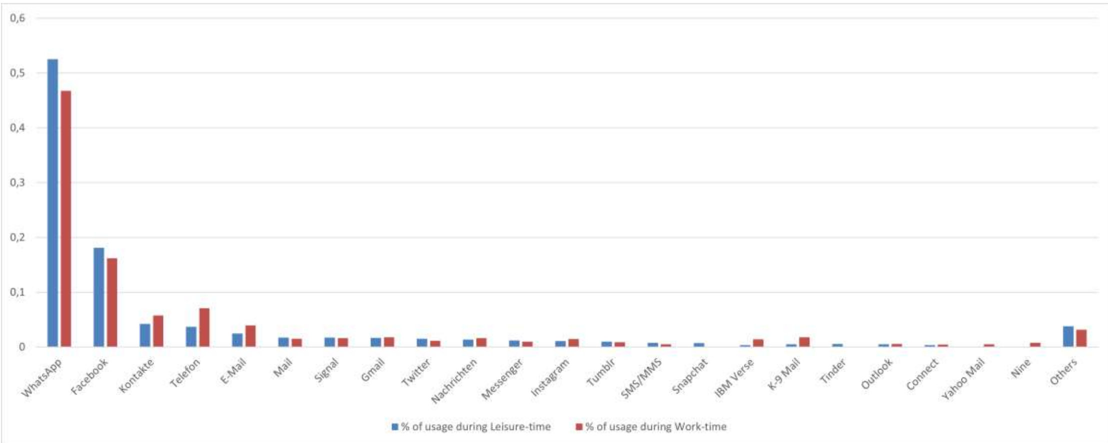
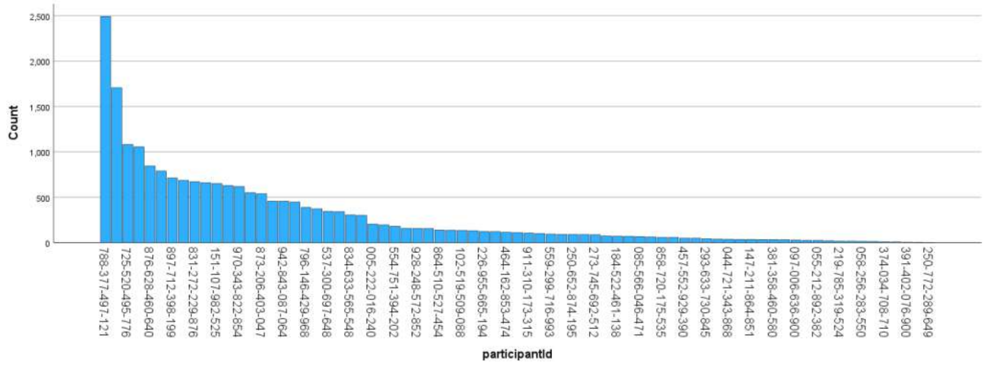


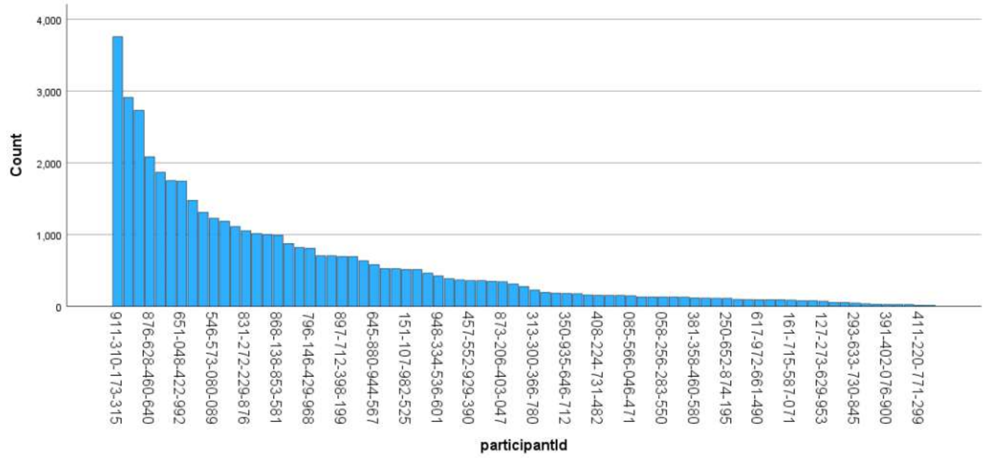

Figure 3.14: Work-time vs. Leisure-time: Frequency per Communication App Chart.

Finally, in Figure 3.15 there are all the participants and their respective frequency of communication app checking depicted in a descending order. Clearly, not all participants have the same checking behaviour. A small number of them (12% for leisure-time and 11% for work-time) tend to check the communication apps very frequently, another handful of them (27% for leisure-time and 21% for work-time) check them not so often, while others (61% for leisure-time and 68% for work-time) do it rarely. However, what is interesting is that their behaviour changes from one domain to the other, meaning that those specific participants who are frequent checkers during leisure-time, not necessarily behave the same during work-time.

One possible analysis of this finding could be that some users may engage in frequent, short bursts of app usage throughout the day, such as quickly checking their communication apps for updates or notifications but may not spend prolonged periods of time on these apps. This could be an indication that people prefer to use these apps for brief, quick interactions, or communication needs, rather than prolonged sessions of usage. A further possible explanation might be that some users prioritize frequent checking of their communication apps to stay connected and updated, but may not have extended periods of leisure-time to engage in longer duration of app usage. This may be an indicator of a busy lifestyle where users may have limited time for prolonged app usage, but still prioritize staying connected through frequent interactions on these apps.




(a) Work-time




(b) Leisure-time

Figure 3.15: Work-time vs. Leisure-time: Frequency per Participant Chart.

### Smartphone Communication App Usage in Terms of Duration

For the graphical representation of the time spent on communication apps, the total amount of duration for all participants over 24 slots can be seen in Figure 3.16 depicted in a multiple-line chart. Visible is that the amount of time that users spend on communication apps during work-time sees a spike from 10 o'clock which remains almost constant up to 16 o'clock. On the other hand, during leisure-time, the duration increases abruptly from 4 o'clock to 7 o'clock, and then more slowly until it reaches the first peak of the day at 13 o'clock, around lunchtime. Once the regular work hours would conclude it can be noticed how duration with regard to work decreases while leisure all of a sudden rises up to the second and highest peak at 21 o'clock, right before sleep time when users might allocate more time for longer activities before concluding their day.

To draw a comparison, the spikes and duration distribution of both domains follow a very similar pattern to the ones depicted in Section 3.6.3. This suggests that the frequency and duration relate with one another, thus supporting the second and fourth hypotheses previously tested and retained.

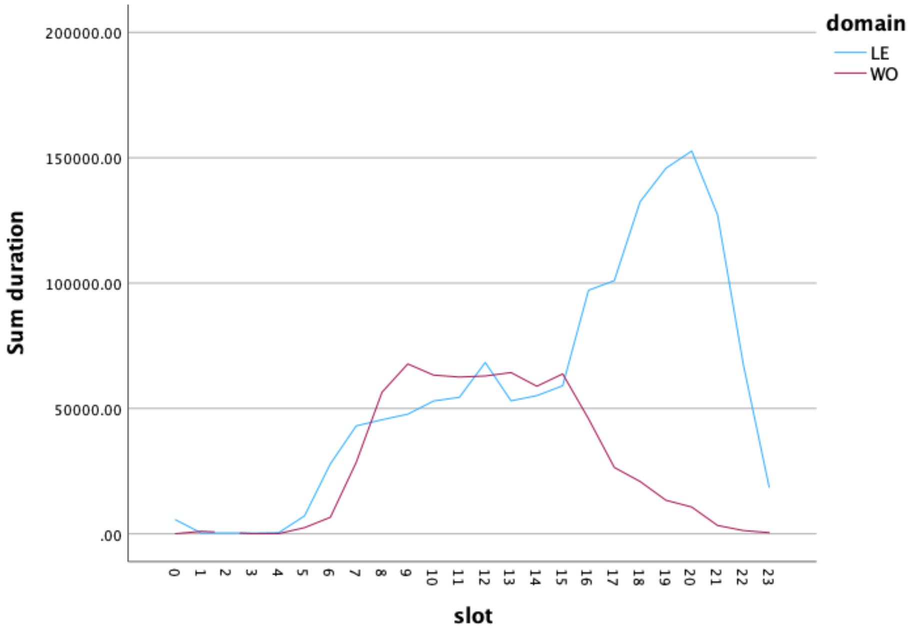



Figure 3.16: Leisure-time vs. Work-time: Duration per Slot Chart.

In Figure 3.17 the usage of communication apps in terms of duration are depicted during leisure-time and work-time. The zoomed-in figures can be found in Appendix A.4. Quite similar to the frequency area charts in Figure 3.14, in both domains WhatsApp and Facebook hold the greater part of app usage with a higher difference visible on WhatsApp compared to Facebook where duration is almost the same.

During work-time, most time is spent on communication apps that can be used for work purposes as well, such as mail, call and messaging services. Nevertheless, Instagram and Gmail seem to be preferred in a comparable way while at work as during leisure. On the other hand, during leisure-time, social media apps take up most of the time spent also including some mailing apps as well. Among the favoured apps are Tinder, Snapchat which engage the user visually more through media in form of photo or video, and Tumblr which is categorized as a micro-blogging app by allowing users to post multimedia content and read short-blogs.

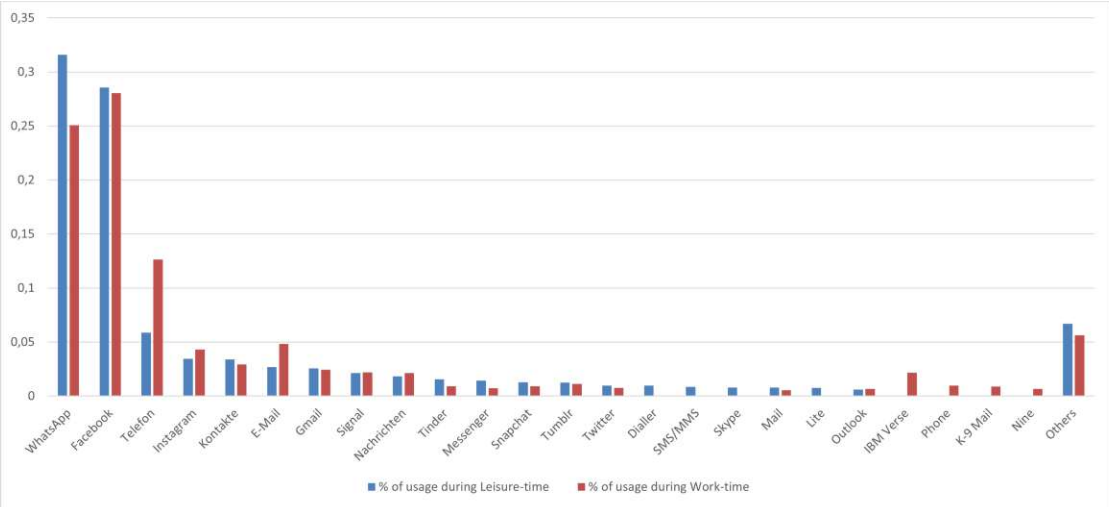
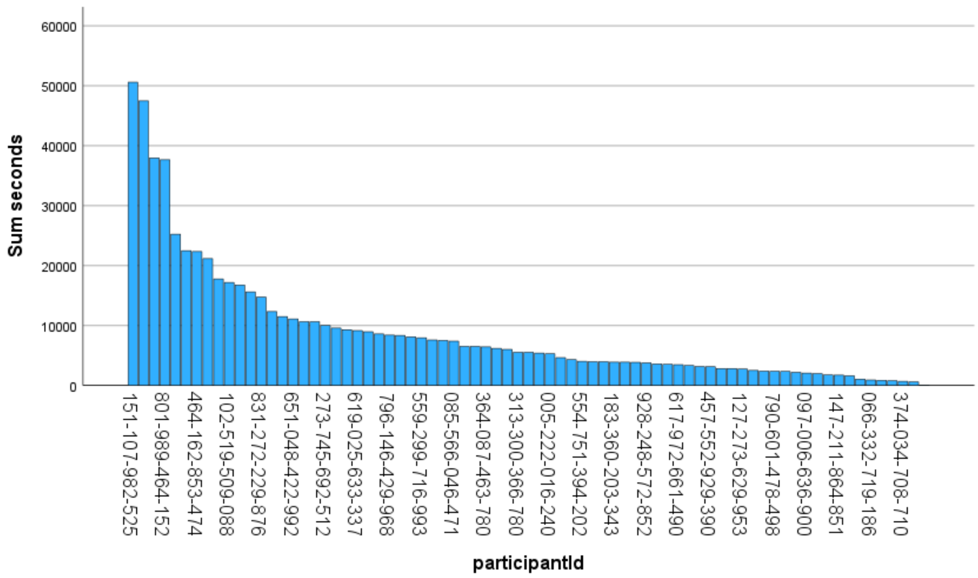


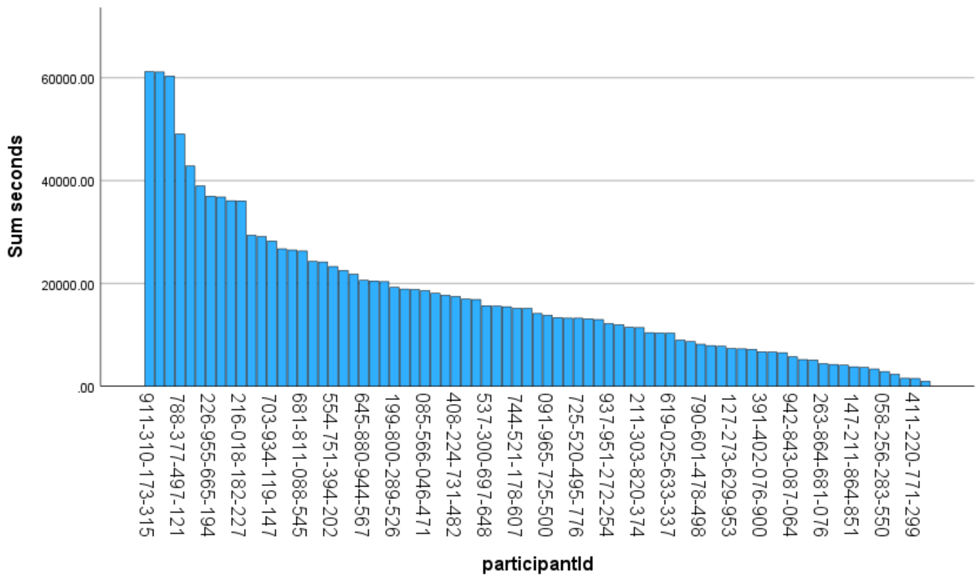

Figure 3.17: Leisure-time vs. Work-time: Duration per Communication App Chart.

Finally, in the bar chart from Figure 3.18, all the participants and their respective time spent on communication apps is depicted in a descending order. As it can be seen, during leisure-time, the number of participants who spend more time on these is higher than in work-time with a more abrupt decrease of the usage in terms of duration. Additionally, by looking at the sum of seconds which represents the sum of duration over the whole study period indicates that users at leisure spend up to 10000 seconds more compared to when being at work, indicating that more time is allocated for this type of activity but also that more social connection might be needed. Further, another aspect is the change in behaviour on participant level when switching the context. Users that are spending the most time engaging with communication apps at work are different than the ones at leisure.

To better understand the behaviour in terms of duration we clustered the users based on this measurement variable. The results show that the majority of users during leisure-time are in a proportion of 45.50% with an average of 15389 seconds whereas for work-time the proportion decreases to 34.70% with an average of only 5560 seconds. One reason for this might be the logging period of the users. Not all of them started on the same day, therefore some may have more free days. As expected, in both domains the preferred app was WhatsApp. Lastly, the second highest group of users during leisure-time was in proportion of 29.90% with an even higher average of 24040 seconds whereas during work-time accounted for 21.30% of the users with an average of 9279 seconds. In this case the chosen app was in both cases Facebook. The considerable differences in the average duration indicate users are aware of the context they are in and change their behaviour - consciously or not - in terms of duration.




(a) Work-time



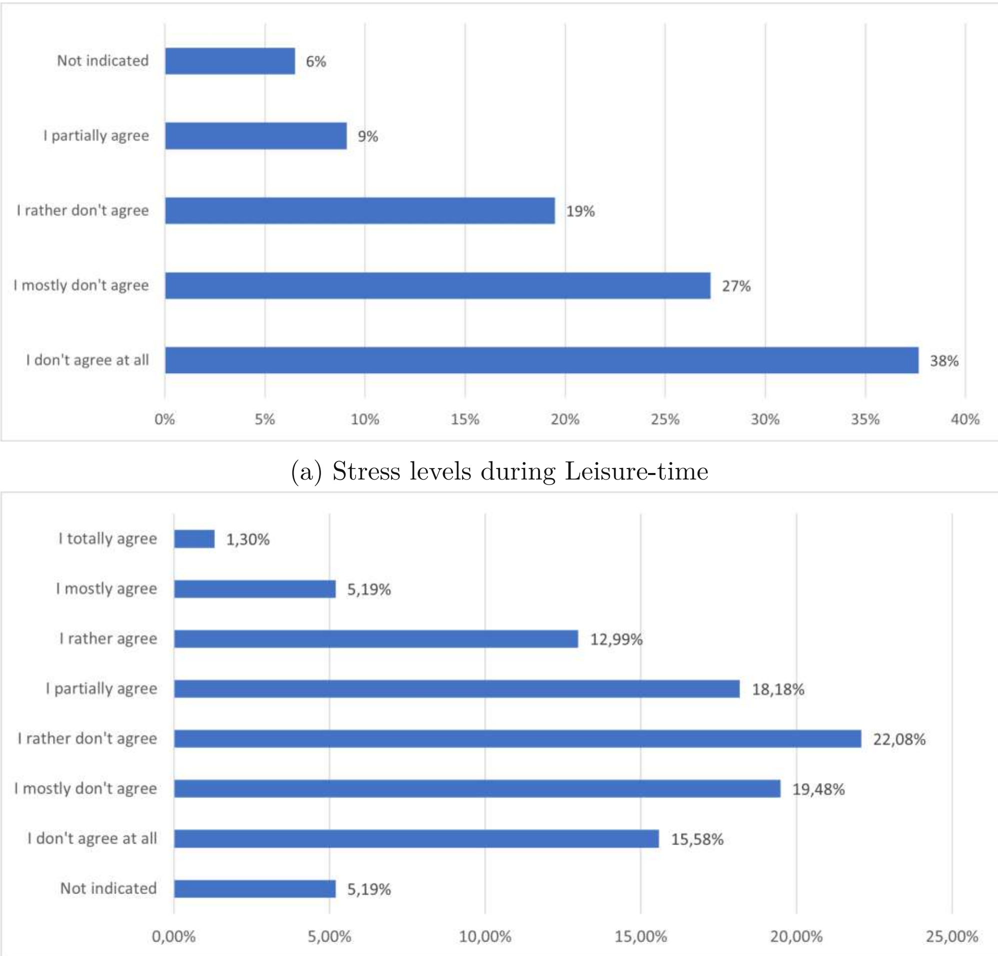

(b) Leisure-time

Figure 3.18: Work-time vs. Leisure-time: Duration per Participant Chart.

### Stress Levels: Leisure-time vs. Work-time

The participants were asked about their stress levels during leisure-time and work-time for the previous day, and the results in the Sections 3.6.1 and 3.6.3 showed interesting patterns for each domain's clusters. Now, to gain a deeper understanding of stress levels across individuals, it is essential to look at each individual response in addition to the mean of a Likert scale. The approach allows for a more thorough investigation of which responses to stress are more widespread in each domain.

During leisure-time, only 9% of the participants agreed partially that they were feeling stressed. A majority of 46% did not agree partially or mostly, whereas 38% did not agree at all, indicating that they were not stressed during leisure-time. The results indicate that the participants did not report much stress during their leisure-time. The majority of the participants did not display significant signs of stress, and those who did were predominantly men in their 30s.




(a) Stress levels during Leisure-time

(b) Stress levels during Work-time

Figure 3.19: Stress levels during Leisure-time and Work-time.

On the other hand, during work-time, a higher percentage of participants, 36% in total, rather agreed, partially agreed or mostly agreed that they were feeling stressed. Additionally, 42% participants did rather not agree or mostly not agree, and 16% did not agree at all, indicating that they were relatively stressed during while at work. This suggests that work-related stress may be more prevalent compared to leisure-related stress. Among the participants who felt some kind of stress were men in their 30s, like during leisure-time whereas for those not experiencing it were men in their 40s. As it can be seen in Figure 3.19 the input was more diverse and granular for work-related perceived stress compared to leisure.

However, the study does not provide information on the specific factors that may be causing stress during work-time or leisure-time. It is unclear whether the stress is related to communication apps, smartphone usage, or private reasons. Further research or additional data may be needed to better understand the underlying causes of stress during these different contexts.

CHAPTER 4

# Discussion

## 4.1 Summary of Results

The research questions of this work aimed at figuring out how users behave with smartphone communication apps in terms of frequency and duration when they are at work or at leisure. The main findings indicated that the environment has an impact on the amount of time spent using communication apps, the frequency of checks, and also the time of day during which these apps are used.

During leisure-time, the first peaks in duration and frequency occurred around 11-13 o'clock and then much higher during 19-21 o'clock. These suggest that users are more likely to use communication apps during breaks at work or after work hours, especially before sleeping. Previous studies have indicated that users tend to scroll through their apps during the afternoon and evening (Oulasvirta et al., 2012), and are more likely to spend more time on their smartphones during late night hours (Battestini et al., 2010; Bohmer et al., 2011). Additionally, research has shown that texting is a more common activity towards the end of the day (Battiston et al., 2016; Bohmer et al., 2011), with a peak in text messages occurring between 16-21 o'clock (Bhih et al., 2016). This work has validated the earlier research, but with a particular emphasis on communication apps, rather than merely general smartphone usage. Further analysis showed that during the 11-13 o'clock time frame, users tended to use communication apps such as Facebook, WhatsApp, Email, and Contacts the most, indicating that these were popular during work breaks to catch up with friends and family, or solve personal matters during lunchtime. During the 19-21 o'clock time frame, the most popular communication apps were Facebook, Instagram, WhatsApp, Snapchat, Twitter, and Telegram, indicating that users have more time to spend with these apps as part of their leisure activities. This finding supports previous research that have stated that communication apps on smartphones are likely to be used throughout the day, with a higher probability in the afternoon and evening, accounting for about 50% of the usage from 11am to 10pm. Specifically, social media apps are more commonly used in the late evening, ranging from 9pm to 1am (Bohmer et al., 2011). Similarly, Jeong et al. (2020) identified that most preferred apps during leisure-time are communication apps including social media and if the users were to open their smartphone and open an app of their choice, the probability for it to be one of these was over 40% compared to other categories like apps for productivity or entertainment. The same behaviour was observed also for users who were engaging in work-related activities during leisure hours.

On the other side, during work-time, participants spent the most time on communication apps between 8-9 o'clock, 12-13 o'clock, and around 15 o'clock. This relates to past research where employees used their smartphones for work in the first part of the day, but engagement in work-related activities was very low compared to non-work activities which was higher after 12pm (Jeong et al., 2020). The most used apps during work-time were Facebook, WhatsApp, text-messaging, and calling. However, the peak at 15 o'clock included Snapchat, Tinder, Twitter, and Tumbler suggesting a cyberslacking behaviour. Alike to our findings, Jeong et al. (2020) measured the probability of app categories that were to be used while at work for both cyberslacking and work-related activities. In both cases communication, instant messaging, and social media apps would be chosen with a probability of over 50% compared to other categories. Additionally, non-work related activities appeared towards the end of the working day when users might be tired and losing focus and motivation or might be procrastinating with the tasks at hand. Among other reasons for engaging in cyberslacking behaviour were a low job satisfaction, having to do very repetitive tasks or conversely requiring a great deal of creativity (Vitak et al., 2011). Moreover, some may use cyberslacking as a coping mechanism to reduce the technostress they experience while at work (Khan & Mahapatra, 2017) developing a compulsive smartphone usage behaviour that in turn would lead to increasing technostress, and thus promoting cyberslacking (Y.-K. Lee et al., 2014). Overall, the blurred boundaries between the leisure and working domain can be noticed in our results as well, hence supporting previous research (Williams, 2019) and emphasizing that organisations should find solutions to reduce cyberslacking by understanding its causes and actively work together with their employees to improve it.

The data indicates that users spend a significant amount of time using smartphone communication apps during both leisure- and work-time. The usage of communication apps was found to be higher during leisure-time compared to work-time, as research had also shown for the smartphone usage in general (Oulasvirta et al., 2012). The average time spent using communication apps is approximately 26 minutes during leisure-time and 20 minutes during work-time, with no significant difference between weekdays and weekends. Additionally, users tend to check their smartphones around 49 times per day in leisure-time, and with 35 checks during work-time. Compared to previous research where average smartphone usage duration was over 160 minutes per day (Deng et al., 2019; Montag, Błaszkiewicz, Lachmann, et al., 2015), our results show that users were engaging in a more balanced behaviour in terms of duration. However, the number of participants and time frame of the study could also be potential reasons for the identified differences. Interestingly, in terms of frequency the results align with literature, which determined a minimum of 60 checks per day (Bohmer et al., 2011) and an overall decrease in the duration of app sessions (Monge Roffarello & De Russis, 2022), thus an increased checking behaviour. This highlights the importance of further investigating the checking behaviour of users along with its relation to duration, as it might reveal more insights about unhealthy usage, which was noticed in this work as well. The excessive behaviour observed in some users who spend up to 3.1 hours and 527 checks per day during work-time, and up to 4.8 hours and 676 checks during leisure-time, could indicate problematic smartphone usage. This may be due to the addictive nature of social media platforms or the convenience of having constant access to communication channels (Kemp, 2023). Further research and interventions may be needed to address this issue.

The exploratory analysis of the duration during leisure-time and work-time revealed that users tend to spend their time on communication apps with frequent sequences of short duration, with the majority of app usage sessions lasting mainly up to a minute and then up to five minutes. For sessions that last longer than five minutes the number dropped significantly. This suggests that users engage in quick interactions or communication, possibly checking notifications or responding to messages in brief bursts of app usage. This behaviour aligns with the earlier findings on app checking frequency, indicating that users prefer frequent, short sessions of app usage lasting between 10 to 250 seconds (Bohmer et al., 2011; Falaki et al., 2010). This type of behaviour has been described as a micro-usage behaviour which has been shown by previous studies to be triggered 18% of time due to not having anything else better to do and thus just "killing time" (Ferreira et al., 2014). Other research have revealed that the frequency of smartphone interactions, rather than the duration of use, is a critical factor in determining the potential for addictive behaviour (Shin & Lee, 2005), that is why it would be important for further research to explore this pattern.

Continuing with the frequency of communications apps usage, Hypothesis 1 in Section 3.5.1 and Hypothesis 3 in Section 3.5.2 found support that shows that the frequency is varying from day to day in both domains without having a recurring pattern among users. Engaging in an arbitrary behaviour of communication apps checking is caused by a variety of reasons.

Firstly, the habitual use of smartphones has led users to form a checking habit that triggers them to check their smartphones even in moments when it is set on silent (Oulasvirta et al., 2012). This indicates that although users are conscious about not wanting to be disturbed by incoming notifications, emails, or calls, they cannot resist the temptation to have a quick look to see if they missed out on any news (Marciano & Camerini, 2022). Consequently, the micro-usage behaviour (Ferreira et al., 2014) has installed as a reaction to FOMO (Marciano & Camerini, 2022) which after sufficient repetition becomes a natural reflex (Heitmayer & Lahlou, 2021) like putting the hand over the mouth when yawning. Developing an innate habit to unconsciously engage with the smartphone brings users to use it every time they are bored, or need to kill time (Ferreira et al., 2014; Heitmayer & Lahlou, 2021) like for example waiting in line at the grocery shop. Being allured to use the smartphone based on disposition, the invariability of the checking pattern from day to day is also related to users' daily routine (Battiston et al., 2016) which can be affected by unplanned situations that can occur, and thus forces users to adapt their plans and implicitly their behaviour of checking, supporting our results.

Secondly, a very important part is played by the purposeful design of communication apps to keep the users engaged and always come back for rewards in form of updates, or new messages from their community (Ferreira et al., 2014). Previous research determined that over 60% of smartphone usage is initiated by incoming notifications of communication apps (Ferreira et al., 2014; Pielot et al., 2014) which did not show a regular occurring pattern, adhering to the idea that a substantial part of the users' engagements is on request in addition to the above mentioned bursts of usage caused by developed habits. Furthermore, Pielot et al. (2014) identified that users respond to incoming notifications twice as fast during weekdays compared to weekends by sticking to the immediate response rule (Holtgraves & Paul, 2013) or feeling the need to act as fast their devices (Porter & Kakabadse, 2006), therefore clearly depicting a change in behaviour from one day to the other, and thus aligning with our hypotheses results.

Lastly, the invariability of frequency checks during leisure-time and work-time is determined also by the mood and the stress that users perceive in the specific context. On the one hand, while at work, users who experience technostress are inclined to engage in cyberslacking activities, thus having an additional reason to engage with their smartphones as a response to the distress felt (Khan & Mahapatra, 2017). Furthermore, when they lack focus with the tasks at hand, users again engage in non-work-related activities during work-time contributing to the rise of checks (Jeong et al., 2020). On the other hand, users at leisure not only have more time to allocate on checking their smartphones but they use it very frequently when they don't have anything better to do (Ferreira et al., 2014; Jeong et al., 2020). Overall, these findings align with ours, showing that although the frequency of checking represents a habitual behaviour or reaction to the system design of the communication apps, the unpredictability of the moods and situations that trigger it also influence the variability that displays a change from day to day.

One of the conclusions drawn from Chapter 3 is that there is a positive relation between the time spent and the checking of communication apps during leisure-time as well as during work-time, which was tested by Hypothesis 2 in Section 3.5.1 and Hypothesis 4 in Section 3.5.2 respectively for each domain. The literature reviewed has shown that there is a positive correlation between the amount of time spent each day using a smartphone and the number of app changes made by users (Deng et al., 2019; Marciano & Camerini, 2022). Other studies have also shown a correlation between the frequency and duration of smartphone usage and problematic smartphone usage. According to research, individuals who are addicted to smartphones tend to spend twice as much time on their devices as non-addicted users and interact with apps twice as frequently (Tossell et al., 2015), emphasizing the link between problematic smartphone usage and the interdependent nature of frequency and duration. Furthermore, by investigating the types of behaviour employees engage in during work-time, it was identified that the distribution pattern of usage time was not showing any significant difference to the distribution pattern of the sessions frequency (Jeong et al., 2020). However, these findings were related to smartphones in general, and not specifically to communication apps or distinguishing between leisure and work domains as this work has focused on.

The main factor driving the positive relation between duration and frequency is the nature of communication apps which provide constant updates to the user. They are designed to encourage frequent checking, such as through push notifications or badges and may contribute to the development of habitual patterns of behaviour. A high flow of notifications create a sense of urgency where users adopt the immediate response rule (Holtgraves & Paul, 2013), and engage with the communication app, most probably spending more time than they would think thus underestimating the time they spend on their smartphones (Duke & Montag, 2017). The checking habit and micro-usage behaviour which users form either through incoming notifications or boredom (Ferreira et al., 2014; Oulasvirta et al., 2012) also have an impact on increasing the frequency at which users check their communication apps, and implicitly contributing to the overall usage time. Additionally, regularly usage of social networking and communication apps, may create "gateway habits" that increase overall smartphone use (Oulasvirta et al., 2012).

The above supported relation between duration and frequency can be also observed from a communication app perspective. In both domains WhatsApp and Facebook are the top 2 most used apps in terms of duration and frequency with WhatsApp being the driving force. They extend over the context and make up the highest proportion of communication apps usage overall. If we look at the measurement variables separately, we could recognize a similar behaviour in both domains. Users check WhatsApp at a much higher frequency, and they spend overall less time than on Facebook, indicating that the purpose of the apps is different. Whereas WhatsApp is preferred for exchanging short messages like over SMS, Facebook invites users to spend more time by providing in addition further services (Montag, Błaszkiewicz, Sariyska, et al., 2015). Within the leisure domain, females in their 40s were the ones who used mostly WhatsApp while for Facebook it was males in their 30s. However, in the work domain the age range for WhatsApp extends to 40s as well, with women being still the highest users, whereas for Facebook it was males up to 30s. Our results align with the ones from Montag, Błaszkiewicz, Sariyska, et al. (2015) where WhatsApp wins over Facebook in terms of use in general with females being more active than men, and Pielot et al. (2014) where it was identified that most notifications were generated by WhatsApp, thus supporting the higher frequency of use determined by us.

Further apps that received a considerate and similar attention in both domains are the email provider apps. In this case, however, duration and frequency displayed very close measurements within but also across both domains, indicating that users allocate time to read and write emails when they access it. Similarly, Pielot et al. (2014) identified emails were the second highest category after texting and calling apps that provide users with notifications at which they react fast. What is more, our results also show that some users were using the work email during leisure hours aligning with the results from Jeong et al. (2020) where the highest probability to engage in work-related activities during leisure-time is due to communications apps including email.

Other categories of apps like the ones for entertainment and productivity are not so attractive for users, thus holding lower values. Nevertheless, what we observed is that Instagram and Twitter are often used during work-time, and therefore supporting a previous finding where these apps hold the highest probability to be checked when engaging in cyberslacking activities (Jeong et al., 2020).

Overall, the results suggest that the choice of communication apps checked during work-time and leisure-time may vary, with a greater emphasis on work-related communication during work-time and social media communication during leisure-time. However, the continued use of mailing apps during leisure-time also highlights the ongoing importance of email as a communication tool in individuals' daily lives, and the dynamic nature of app usage behaviours in different contexts.

Furthermore, the behaviour our users engage in may reflect a blurring of boundaries between work and leisure (Derks & Bakker, 2014), with individuals increasingly using communication apps for both personal and work-related purposes mixing their private and professional life. This could be attributed to the changing nature of work and the widespread use of smartphones that enable constant connectivity (Kane, 2015), allowing individuals to check their communication apps during leisure-time and vice-versa. This has led to the rise of cyberslacking behaviour during work-time (McBride et al., 2015) causing serious concern as it was shown to be related to technostress, and used as a coping mechanism to the distress felt by it (Güğerçin, 2020). What is more, within the leisure domain it could be related to anxiety (Thomée et al., 2010) and a cause for sleep disorders (Thomée et al., 2011).

Another interesting finding from Section 3.6 is regarding the users' different behaviour from one another and in different domains as well. The results indicate that there is considerable variability in the frequency of communication app checking among participants, with some individuals checking these apps very frequently, some checking them less often, and others rarely checking them. In addition to the frequency of communication app checking, there is also noticeable variability in the duration of time spent on these apps. Some individuals may spend only a few minutes per day on these apps, while others may spend several hours per day. This variability suggests that different individuals may have distinct patterns of app usage and they may depend on various factors, including personal preferences, work or social obligations, and other individual factors.

Another intriguing observation is that participants' checking behaviour appears to change between the work-time and leisure-time domains as well. This implies that individuals may have different communication needs and preferences depending on the context they are in. For example, some participants who check communication apps frequently or spend time on them during leisure-time may not exhibit the same behaviour during work-time, indicating that their communication habits may be influenced by the nature of their activities or responsibilities during different times of the day.

These findings are supported by previous research that suggests habits are influenced by both the person himself and environment in which they occur (Carden & Wood, 2018). Specifically, habits are shaped by a combination of internal factors including motivation, willpower, social norms, and external factors such as local and temporal context (Wood & Rünger, 2016). Thus, the changes in users' communication app checking behaviour between work-time and leisure-time domains may reflect their differing communication needs and preferences depending on the context.

The differences in communication app checking behaviour between work-time and leisure-time domains could also be seen in the findings regarding the identified groups of users based on their smartphone usage type - private or dual. The *Private Purpose Users* group was prevalent in both leisure and work domains, consisting mainly of males in their 30s and 40s who used WhatsApp and Facebook most frequently. However, the duration and frequency of use differed significantly between the two contexts, with much longer and more frequent use during leisure-time compared to work-time. During leisure-time, these users spent a mean duration of 4.64 hours on communication apps, whereas during work-time, participants engaged in non-work activities and used these apps for a mean duration of 1.64 hours and a mean frequency of 294 checks, indicating cyberslacking behaviour. Additionally, *Dual Purpose Users* group comes second in both work and leisure domains. During leisure-time, the participants were mainly men in their 20s with a mean frequency of 536 checks, and the mean duration of 4.35 hours. In contrast, during work-time, the participants were mainly men in their 30s and 40s with a mean duration of 2.64 hours and a mean frequency of 470 checks. In both groups the mostly used apps were WhatsApp and Facebook.

A noteworthy finding is that the study identified two distinct groups of excessive smartphone users based on their usage during leisure- and work-time. The first group, known as the *Dual Purpose Excessive Users*, consisted of participants who used their smartphones excessively in both private and professional modes during leisure-time, mainly women in their 30s. WhatsApp and Facebook were the most used apps in this group, and the excessive usage during leisure-time is not known if it is related to work-related tasks or not since WhatsApp is an app that is available and intended for work purposes as well. However, this could be an indicator of the blurred boundaries between work and leisure in the case of users not being able to separate work and private life from one another (Thomée et al., 2010) as well as the pressure to be available for work at all times (Fonner & Roloff, 2012). The second group, known as the *Private Purpose Excessive*

*Users*, consisted of participants who used their smartphones excessively in private mode during work-time, mainly women in their 30s and 40s. They used mostly WhatsApp and Facebook and had an average duration of 6.9 hours and average frequency of 4.952 checks over the study period, indicating considerate cyberslacking behaviour that could affect job performance and personal well-being (Jeong et al., 2020; Yang, 2021). These findings highlight how the different contexts and purposes for which users employ their smartphones can have a significant impact on their communication habits and may reflect the varying communication needs and preferences of individuals in these contexts.

Furthermore, the results of this work also indicate that there are some interesting trends regarding the relationship between smartphone use and stress levels across different user groups in the work and leisure domains. These suggest that the relationship between smartphone use and stress levels may differ between work-time and leisure-time.

In the work domain, all three groups reported similar stress levels, with average Likert Scale scores ranging from 3.12 for the *Dual Purpose Users*, 3.19 for the *Private Purpose Users* and 3.25 for the *Private Purpose Excessive Users*, hence displaying an increase along with more smartphone usage in terms of duration and frequency. This suggests that smartphone use during work hours may be a contributor to stress levels for all groups despite the neutral attitude identified towards perceived stress. Although we do not know what the causes for it were, we know that the behaviour in which they were engaging could be categorised as cyberslacking due to the private smartphone being used during work-time. Therefore, this could be an indicator relating to the stress levels since a study from 2022 could identify a positive relation between the stress and the inclination to refer to cyberslacking activities at work as a coping mechanism (Mishra & Tageja, 2022). Furthermore, engaging in non-work-related activities was also shown to be positively related to technostress, which is one form of stress (Güğerçin, 2020). If that would be the case, then the high engagement in cyberslacking in our groups might be due to technostress, although more insights would be needed.

In contrast, in the leisure domain, there was some difference in stress levels between the three groups. The *Private Purpose Users* and *Dual Purpose Users*, with average Likert Scale scores of 2.0 and 1.9, respectively. However, the *Dual Excessive Users* group reported a significantly higher average stress level of 2.6. These findings suggest that excessive smartphone use during leisure-time may be contributing to higher stress levels for some users. Since the highest mean of stress perceived is accounted by the group who used the smartphone for professional purposes as well, and previous research has determined that availability expectations outside of regular working hours and the degree of work engagement relate with work-home interference (Derks et al., 2015), it might be a reason for higher perceived stress during leisure-time. Lastly, allowing boundaries to dissolve between private and professional lives was determined to pose a threat to individuals' well-being, thus increasing stress as a potential consequence (Adisa et al., 2017).

Based on our results, it appears that users may experience higher stress levels during work- than during leisure-time. However, it's important to note that these cannot be generalised to all smartphone users, and other factors may also contribute to stress levels in both work and leisure domains.

According to literature, the most probable explanation is that the boundaries between work and personal life are becoming increasingly blurred due to the constant connectivity provided by smartphones (Fonner & Roloff, 2012). As a result, this can lead to an expectation of constant availability and productivity in and outside of working hours (Porter & Kakabadse, 2006), which can contribute to cyberslacking, stress and burnout (Mishra & Tageja, 2022). To conclude, although the behaviour of our user groups could be tied to potential stress creators from available literature, more information on what caused the feeling of stress would be needed to draw a clear conclusion.

## 4.2 Limitations

Limitations are an important element of any research study because they allow for reflection on the challenges and obstacles faced during the research process. By acknowledging these limitations, we may achieve a more thorough understanding of the extent to which the findings of our work can be applied to other settings and suggest areas for future research. In this section, we will delve into our work's numerous constraints and provide a comprehensive explanation of each.

One of the main limitations of our work was that the data was already gathered for us. This meant that we did not have control over the data collection process. Therefore, there may have been important variables that were not included in the data set or were not measured in the way we would have preferred. A possible drawback of our research is that the app tracking data may be unreliable because it is dependent on the hardware setup and software compatibility of the subjects' smartphones. This means that problems beyond our control, such as app failures and flaws in programs, may have impacted the precision of the data gathered.

Moreover, the small sample size of our work may also have bound our ability to detect noteworthy associations and trends in the data. This limitation was compounded by the fact that the original sample size was decreased further after data cleaning, potentially reducing the statistical strength of our work. Our findings may have been more difficult to distinguish between genuine connections and mere occurrences due to the smaller sample size and consequent drop in statistical strength. As a consequence, the generalisation of our findings may be restricted, and future research should strive to include bigger and more varied groups to enhance the results' accurate representation and ability for generalisation.

Our study's consideration of only smartphone users from Germany and Austria was an additional limitation. The generalisation of our results to other populations and cultures may have been hindered by this constrained demographic. Different cultural and societal factors, such as social norms and technology use, may influence communication apps use and the patterns we observed in our study may not necessarily apply to other regions or countries. In order to gain an enhanced understanding of communication apps usage patterns and the factors that influence them, upcoming research might want to include more diverse samples from different geographic regions.

It is particularly important to bear in mind that the collection of data concluded prior to the global epidemic and the widespread adoption of teleworking as we consider the limitations of our research. A significant change in communication apps usage trends could potentially have taken place due to the COVID-19 pandemic's unexpected impact on how people work and interact. We acknowledge that the generalisation of our research to the present post-pandemic period may be constrained in light of this context. Considering that teleworkers depend more on technology for communication and job completion while working distantly, it is foreseeable that teleworking will end up resulting in a corresponding rise in communication apps usage. It is nevertheless significant to point out, however, that the findings we obtained in this work still offer useful information about communication apps usage patterns among German and Austrian users before the outbreak of the pandemic.

One of the most important limitations of our research is that we only looked at empirical data on the frequency and duration of smartphone use as well as the socio-demographics of the users and the daily stress levels of the users in order to describe them. Although more subjective data was collected during the study via daily surveys, it was determined that this would be the case for a future research study. While objective data is helpful in identifying patterns and trends, subjective data is critical for giving a comprehensive image of how smartphone use affects individuals. Our study's lack of subjective data limited our ability to detect possible negative effects of smartphone use. While our research provides useful insights into the quantitative trends of smartphone use among German and Austrian users, it does not provide a comprehensive understanding of the complex connection between smartphone use, mental health, and well-being. This research void requires future studies which incorporate both objective and subjective data in order to better capture the complex nature of smartphone use and its possible effects on people.

Last but not least, despite the fact that we examined a number of patterns in the research we conducted employing a theoretical framework, there are a few more patterns that could potentially be investigated in subsequent studies. Our research was restricted to examining only three distinct patterns, and there are other significant patterns that we overlooked which did come by in our literature review process and were mentioned in the theoretical background of this work. Future studies could broaden the scope of pattern analysis and explore the connections between various patterns and problematic smartphone use as well as other variables like psychological characteristics of the users.

To conclude, we expect that by addressing the limitations of the research we have conducted, other researchers will be encouraged to expand on our findings and explore the different aspects of smartphone communication apps usage in greater depth - in work and leisure domains. In order to ensure the outcomes are more accurately representative of the general population, increasing the sample size and diversifying the participants would be two significant priorities for advancement. Future studies should additionally take into consideration how the use of communication apps is affected by teleworking and the post-pandemic environment, which we were unable to investigate simply because of the timing of our data collection.

By addressing these limitations, future studies can provide a deeper and more precise understanding of communication apps use and its potential impact on individuals' mental and physical health.

## 4.3 Implications and Future Research

The findings of our work add to the ongoing research in the area of smartphone usage behaviour with a focus on communication apps only, clearly exposing users' behaviour in terms of frequency, duration, app preferences, and smartphone usage purpose within and across the leisure and work domains.

Our results support existing theories which state that smartphones are habit forming devices and contribute to it by highlighting that users change their communication app behaviour when switching from leisure-time to work-time in terms of frequency and duration of use. Being at leisure affects the behaviour by increasing communication apps usage when compared to being at work. Nevertheless, we identified a similarity about frequency across both domains, namely that around midday, users engage in an almost identical checking behaviour with communication apps.

One aspect that goes beyond context and has power over it, is the choice in apps. WhatsApp and Facebook remain the top 2 most used apps in terms of frequency and duration across both domains. With this we emphasize that social connection and constant communication with family, friends, and colleagues remains a constant during leisure and working hours. What is more, email provider apps receive a similar degree of attention in both domains, indicating a very balanced behaviour regarding frequency and duration. This indicates that email apps have found their use outside of work as well, where individuals continue to use it for personal purposes such as personal communication, online shopping, or news consumption. On the other hand, it could highlight that they carry work matters in personal life, contributing to blurring the boundaries between work and leisure.

By capturing the smartphone usage purpose in our data, we found evidence of cyberslacking behaviour and work-related activities during leisure-time. Our results show that excessive communication apps user groups are comprised of those who user their smartphone for private purpose only during work-time and dual purpose during leisure-time, all engaging mostly with WhatsApp and Facebook.

Overall, these findings lay the foundation for future research of communication apps usage behaviour within a context, their habit-forming nature, and the consequences of them. It is already known that their pervasiveness contributes to blurred boundaries, technostress perceived in both domains, and cyberslacking activities. Nevertheless, more research would be needed to establish if the context alone has a significant impact on users' behaviour. We believe it could be a more complex web of underlying factors that influence it. Therefore, including factors such as personality traits, psychological needs, social norms, workplace availability expectations, and the design of communication apps, a more nuanced and multifaceted explanation could be provided into why communication apps have a habit-forming nature. These would help in tackling productivity, well-being, technostress, and cyberslacking not only in work and leisure domains, but also in organisations. Lastly, future research should include bigger sample sizes of various demographics, as well as more measurement variables of smartphone usage in order to solidify current theoretical and empirical literature of this domain.

CHAPTER 5

# Conclusion

The findings of this work contribute to the research of smartphone communication habits by shedding light on the differences in behaviour between work and leisure contexts. This distinction provides a deeper understanding of the patterns of smartphone use and communication habits, which has not been previously explored in depth. The significance of this research lies in the fact that it focuses solely on smartphone communication habits and how these habits vary across different contexts, providing a deeper understanding of smartphone use.

One important finding is that users tend to spend more time on communication apps during leisure-time than during work-time. Additionally, users exhibit different communication habits in different domains, indicating that context plays a crucial role in shaping users' smartphone communication behaviour. The research also highlighted that different communication apps are used heavily in different domains, with WhatsApp and Facebook being the most frequently used communication apps in both leisure and work domains.

The findings also revealed the presence of cyberslacking behaviour during work-time, where participants engage in non-work activities using communication apps. Furthermore, blurred boundaries between work and leisure contexts were detected, which can have potential implications for users' overall well-being and technostress. in both domains the frequency of app checking was found to vary from day to day, and the duration of use was strongly related with the frequency of app checking.

In terms of future research, this study provides up prospective areas of research by investigating how different context-specific behaviour habits can have different impacts on the overall well-being of individuals and their levels of technostress. Future study might look at ways to handle these differing patterns in communication behaviours across contexts in order to ensure that people have a healthy and productive relationship with their smartphones.

In conclusion, the findings of this work contribute to the understanding of smartphone communication patterns and their relevance to context-specific behaviour. This work emphasizes the significance of considering context while researching smartphone use and communication habits, and it provides insights into how these habits might differ across domains.

APPENDIX A

# Appendix

## A.1 Leisure-time vs. Work-time Charts

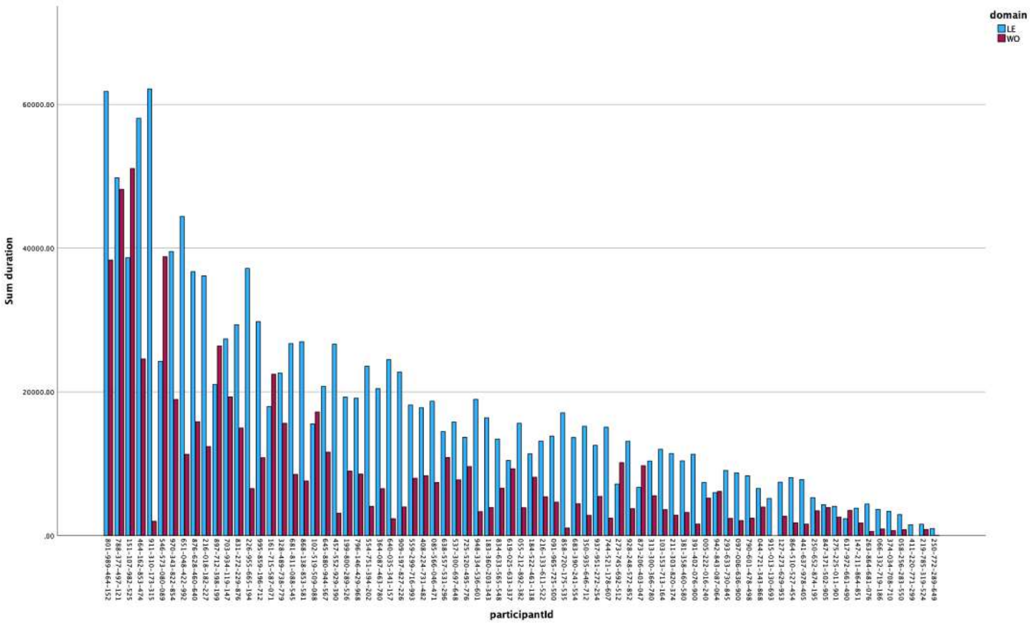



Figure A.1: Leisure-time vs. Work-time: Duration of All Participants.

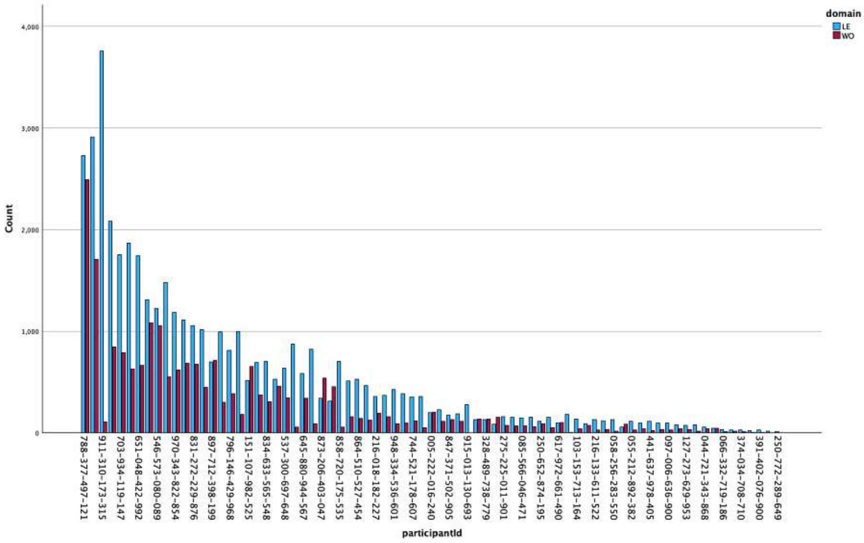



Figure A.2: Leisure-time vs. Work-time: Frequency of All Participants.

## A.2 Leisure-time - H2 Results in R

### A.2.1 Loading and reading data

Read Full Data

```
data = read.csv("LE_Pivot_Freq_Day.csv")
```

Erasing the user name

```
data = data[,-1]
```

Select the frequencies

```
data_test = plyr::llply(.data = c(1:nrow(data)), .fun = function(x){
  aux = data[x,data[x,]!=0]
  data.frame(t = c(1:length(aux)),
             checks=unlist(aux))
}, .parallel = FALSE)
```

Convert data_test to a time series object

```
ts_data <- lapply(data_test, function(x) {
  # Check if there are enough observations for ADF test
  if (length(x$checks) < 4) {
    return(NULL)
  } else {
    return(ts(x$checks, start = 1, frequency = 1))
  }
})
```

Remove NULL values

```
ts_data <- ts_data[!sapply(ts_data, is.null)]
```

### A.2.2 Augmented Dickey–Fuller (ADF) t-statistic tests

Apply ADF test on each time series

```
adf_results <- lapply(ts_data, function(x) adf.test(x))
```

The lapply() function applies the adf.test() function to each time series in the ts_data list, which means that each time series is tested independently. The adf.test() function does not compare each value of a time series to the next one. Instead, it uses a statistical model to test whether the time series as a whole is stationary or non-stationary.

### A.2.3 As we have multiple test we do Bonferroni correction

Define the Bonferroni-corrected significance level

```
alpha <- 0.05/length(adf_results)
```

Create a vector to store the results of the correction

```
adf_results_corrected <- rep(NA, length(adf_results))
```

Apply the correction to each test result

```
for (i in 1:length(adf_results)) {
  if (!is.na(adf_results[[i]]$p.value)
  && adf_results[[i]]$p.value < alpha) {
    adf_results_corrected[i] <- "Reject"
  } else if (!is.na(adf_results[[i]]$p.value)) {
```

```
    adf_results_corrected[i] <- "Fail to reject"
  } else {
    adf_results_corrected[i] <- NA
  }
}
```

Combine the original results and the corrected results into a data frame

```
adf_results_df <- data.frame(Original =

unlist(lapply(adf_results,
          function(x) x$p.value)),
         Corrected = adf_results_corrected)

print(adf_results_df)

##       Original      Corrected
## 1  0.30309087 Fail to reject
## 2  0.09777331 Fail to reject
## 3  0.97136560 Fail to reject
## 4  0.49102322 Fail to reject
## 5  0.01000000 Fail to reject
## 6  0.54896598 Fail to reject
## 7  0.98299382 Fail to reject
## 8  0.31102784 Fail to reject
## 9  0.14131701 Fail to reject
## 10 0.91435004 Fail to reject
## 11 0.71381119 Fail to reject
## 12 0.46562175 Fail to reject
## 13 0.01000000 Fail to reject
## 14 0.04861453 Fail to reject
## 15 0.77396345 Fail to reject
## 16 0.39589434 Fail to reject
## 17 0.38692001 Fail to reject
## 18 0.93683612 Fail to reject
## 19 0.74845403 Fail to reject
## 20 0.67766834 Fail to reject
## 21 0.80533524 Fail to reject
## 22 0.77440531 Fail to reject
## 23 0.64432486 Fail to reject
## 24 0.87912290 Fail to reject
## 25 0.51325076 Fail to reject
## 26 0.95964851 Fail to reject
```

```
## 27 0.76248794 Fail to reject
## 28 0.02120816 Fail to reject
## 29 0.65836658 Fail to reject
## 30 0.52649760 Fail to reject
## 31 0.53392947 Fail to reject
## 32 0.23733021 Fail to reject
## 33 0.89393937 Fail to reject
## 34 0.31907765 Fail to reject
## 35 0.16445583 Fail to reject
## 36 0.05682819 Fail to reject
## 37 0.01000000 Fail to reject
## 38 0.64296922 Fail to reject
## 39 0.72360366 Fail to reject
## 40 0.02308137 Fail to reject
## 41 0.59511672 Fail to reject
## 42 0.04943402 Fail to reject
## 43 0.93500068 Fail to reject
## 44 0.73267792 Fail to reject
## 45 0.01000000 Fail to reject
## 46 0.05533662 Fail to reject
## 47 0.79181156 Fail to reject
## 48 0.04196929 Fail to reject
## 49 0.31083785 Fail to reject
## 50 0.54374749 Fail to reject
## 51 0.18593822 Fail to reject
## 52 0.04882538 Fail to reject
## 53 0.02693573 Fail to reject
## 54 0.98056505 Fail to reject
## 55 0.76718167 Fail to reject
## 56 0.25440337 Fail to reject
## 57 0.45577255 Fail to reject
## 58 0.97524381 Fail to reject
## 59 0.64822758 Fail to reject
## 60 0.37755027 Fail to reject
## 61 0.79409064 Fail to reject
## 62 0.81492863 Fail to reject
## 63 0.02027427 Fail to reject
## 64 0.99000000 Fail to reject
## 65 0.96606228 Fail to reject
## 66 0.91797916 Fail to reject
## 67 0.45585982 Fail to reject
## 68 0.73059012 Fail to reject
## 69 0.26958828 Fail to reject
```

```
## 70 0.94274665 Fail to reject
## 71 0.77854343 Fail to reject
## 72 0.36043873 Fail to reject
## 73 0.01277686 Fail to reject
## 74 0.12183160 Fail to reject
## 75 0.28464810 Fail to reject
## 76 0.88866480 Fail to reject
## 77 0.40146205 Fail to reject
```

**None of the test are smaller than 0.05/75, thus we support the Hypothesis: the frequency of communication apps activations varies from day to day during leisure-time.**

### A.2.4 Plotting results

Extract the p-values from the adf_results list

```
p_values <- sapply(adf_results, function(x) x$p.value)
```

Set the size of the plot

```
png("plot.png", width = 1000, height = 600)
```

Create a bar plot of the p-values with adjusted margins

```
barplot(p_values, names.arg = names(ts_data),
        main = "ADF Test Results",
        ylab = "p-value", col = "blue",
        mar=c(5, 5, 2, 2))
```

## A.3 Work-time - H4 Results in R

### A.3.1 Loading and reading data

Read Full Data

```
data = read.csv("WO_Pivot_Freq_Day.csv")
```

Erasing the user name

```
data = data[,-1]
```

Select the frequencies

```
data_test = plyr::llply(.data = c(1:nrow(data)), .fun = function(x){
  aux = data[x,data[x,]!=0]
  data.frame(t = c(1:length(aux)),
             checks=unlist(aux))
}, .parallel = FALSE)
```

Convert data_test to a time series object

```
ts_data <- lapply(data_test, function(x) {
  # Check if there are enough observations for ADF test
  if (length(x$checks) <= 6) {
    return(NULL)
  } else {
    return(ts(x$checks, start = 1, frequency = 1))
  }
})
```

Remove NULL values

```
ts_data <- ts_data[!sapply(ts_data, is.null)]
```

### A.3.2 Augmented Dickey–Fuller (ADF) t-statistic tests

Apply ADF test on each time series

```
adf_results <- lapply(ts_data, function(x) adf.test(x))
```

The lapply() function applies the adf.test() function to each time series in the ts_data list, which means that each time series is tested independently. The adf.test() function does not compare each value of a time series to the next one. Instead, it uses a statistical model to test whether the time series as a whole is stationary or non-stationary.

### A.3.3 As we have multiple test we do Bonferroni correction

Define the Bonferroni-corrected significance level

```
alpha <- 0.05/length(adf_results)
```

Create a vector to store the results of the correction

```
adf_results_corrected <- rep(NA, length(adf_results))
```

Apply the correction to each test result

```
for (i in 1:length(adf_results)) {
  if (!is.na(adf_results[[i]]$p.value)
  && adf_results[[i]]$p.value < alpha) {
    adf_results_corrected[i] <- "Reject"
  } else if (!is.na(adf_results[[i]]$p.value)) {
    adf_results_corrected[i] <- "Fail to reject"
  } else {
    adf_results_corrected[i] <- NA
  }
}
```

Combine the original results and the corrected results into a data frame

```
adf_results_df <- data.frame(Original =
unlist(lapply(adf_results, function(x)
                             Corrected = adf_results_corrected)

print(adf_results_df)

##      Original      Corrected
## 1  0.64315165 Fail to reject
## 2  0.97503495 Fail to reject
## 3  0.10557190 Fail to reject
## 4  0.99000000 Fail to reject
## 5  0.79544567 Fail to reject
## 6  0.32367262 Fail to reject
## 7  0.90680614 Fail to reject
## 8  0.78776221 Fail to reject
## 9  0.40001054 Fail to reject
## 10 0.71146795 Fail to reject
## 11 0.85469120 Fail to reject
## 12 0.01000000 Fail to reject
## 13 0.97592072 Fail to reject
## 14 0.47497753 Fail to reject
## 15 0.88621776 Fail to reject
## 16 0.97910100 Fail to reject
## 17 0.01000000 Fail to reject
## 18 0.08414185 Fail to reject
```

```
## 19 0.10877934 Fail to reject
## 20 0.03580527 Fail to reject
## 21 0.01000000 Fail to reject
## 22 0.99000000 Fail to reject
## 23 0.63993689 Fail to reject
## 24 0.95270391 Fail to reject
## 25 0.99000000 Fail to reject
## 26 0.44241663 Fail to reject
## 27 0.01000000 Fail to reject
## 28 0.97623372 Fail to reject
## 29 0.42630829 Fail to reject
## 30 0.97044437 Fail to reject
## 31 0.85910872 Fail to reject
## 32 0.01000000 Fail to reject
## 33 0.50721654 Fail to reject
## 34 0.72567843 Fail to reject
## 35 0.68579176 Fail to reject
## 36 0.01000000 Fail to reject
## 37 0.56253166 Fail to reject
## 38 0.91536653 Fail to reject
## 39 0.35551514 Fail to reject
## 40 0.51417836 Fail to reject
## 41 0.93396499 Fail to reject
## 42 0.01000000 Fail to reject
## 43 0.65726958 Fail to reject
## 44 0.81704794 Fail to reject
## 45 0.98814200 Fail to reject
## 46 0.59989875 Fail to reject
```

**None of the tests are smaller than 0.05/75, thus we DON'T reject the null of non-stationarity.**

### A.3.4 Plotting results

Extract the p-values from the adf_results list

```
p_values <- sapply(adf_results, function(x) x$p.value)
```

Set the size of the plot

```
png("plot.png", width = 1000, height = 600)
```

Create a bar plot of the p-values with adjusted margins

```
barplot(p_values, names.arg = names(ts_data),
        main = "ADF Test Results",
        ylab = "p-value", col = "blue",
        mar=c(5, 5, 2, 2))
```

## A.4 Duration per Communication App Charts

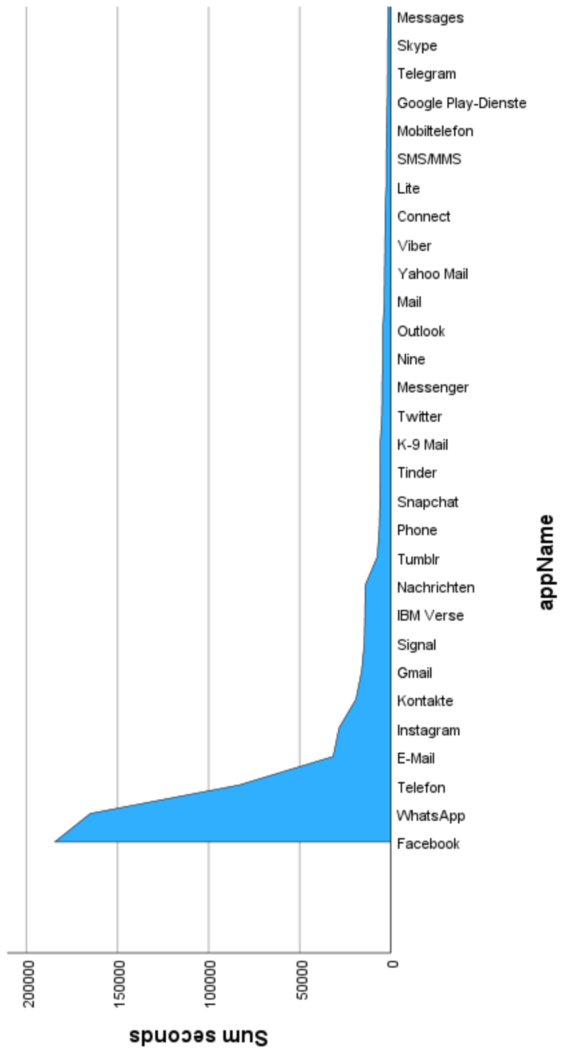



Figure A.3: Work-time: Duration per Communication App Chart.

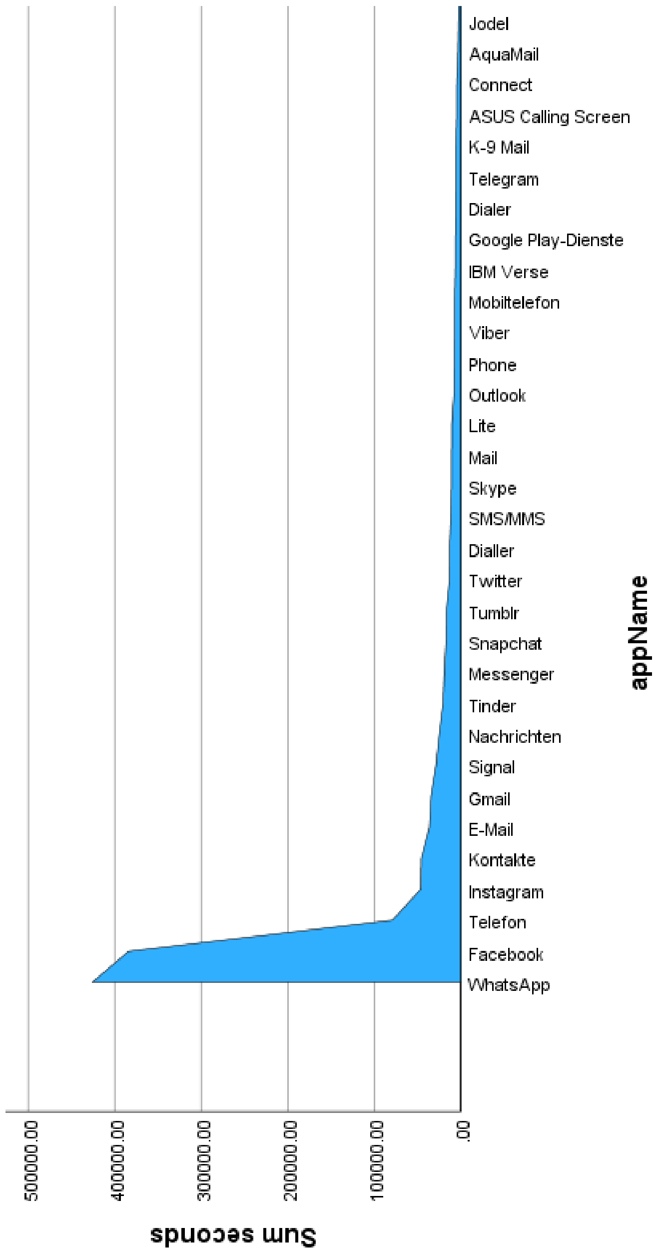



Figure A.4: Leisure-time: Duration per Communication App Chart.

## A.5 Frequency per Communication App Charts

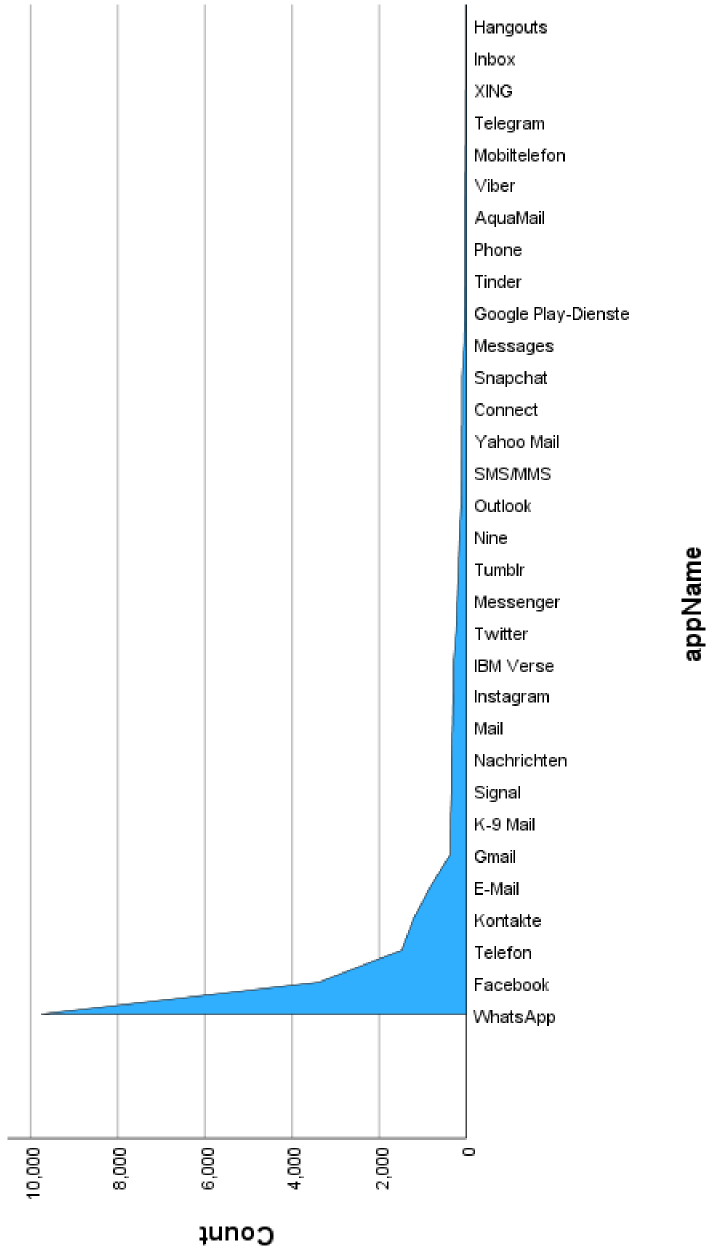



Figure A.5: Work-time: Frequency per Communication App Chart.

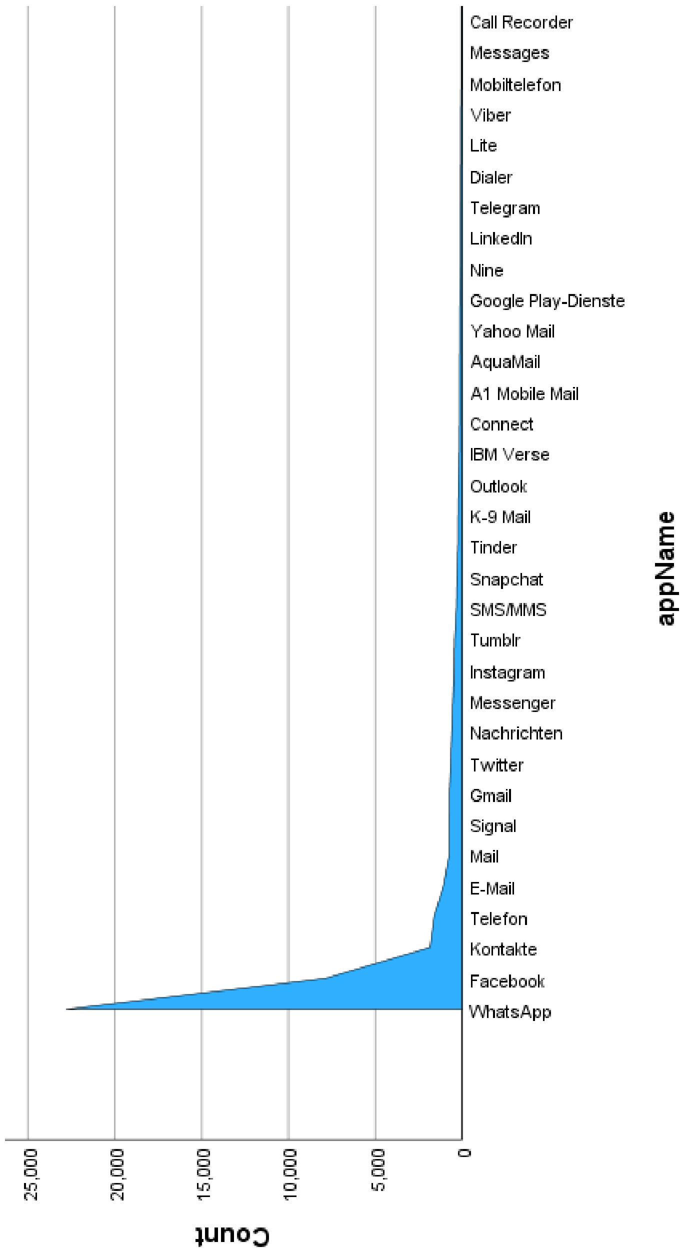
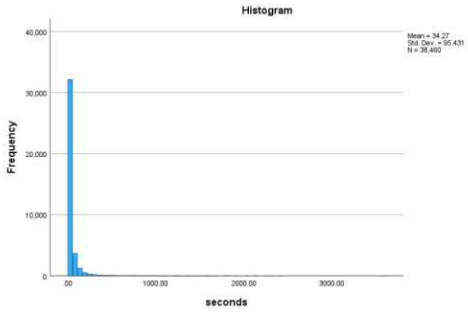
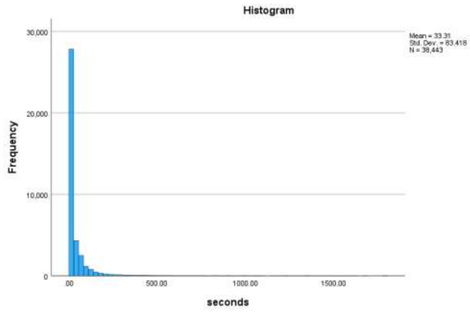



Figure A.6: Leisure-time: Frequency per Communication App Chart.

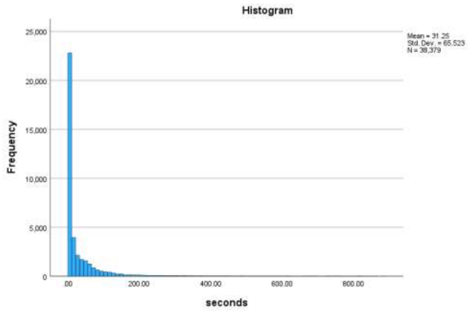
## A.6 Leisure-time Histograms



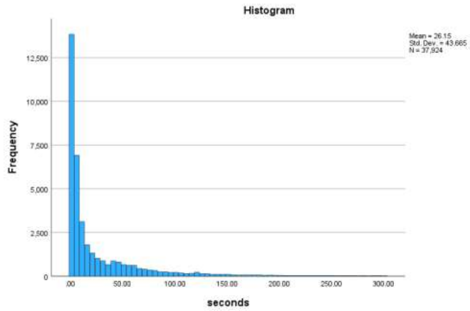

(a) Up to 1 hour.



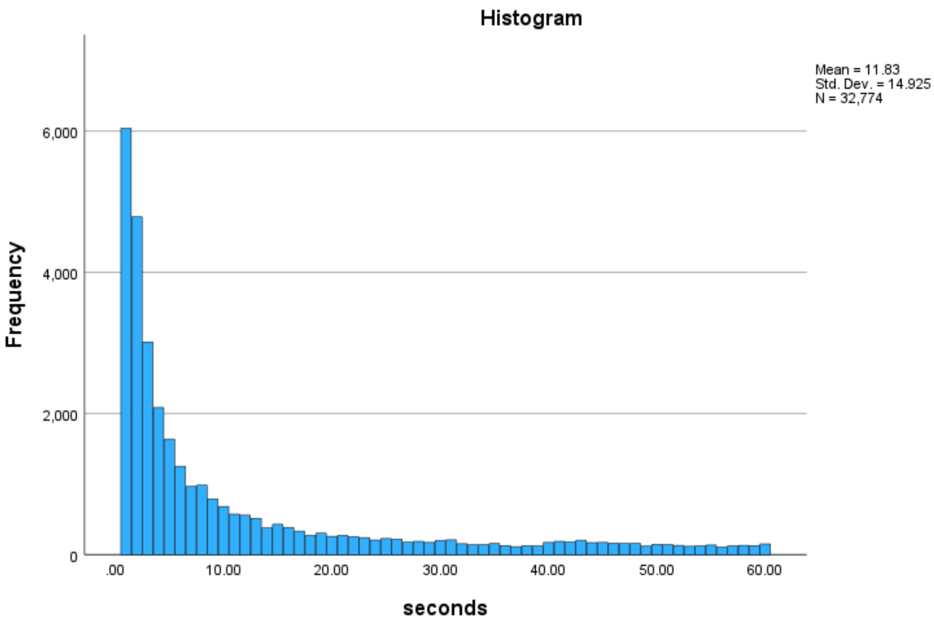

(b) Up to 30 minutes.




(c) Up to 15 minutes.



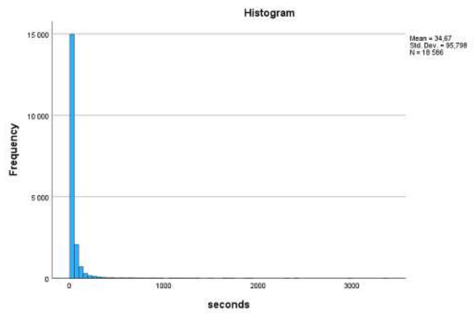

(d) Up to 5 minutes.



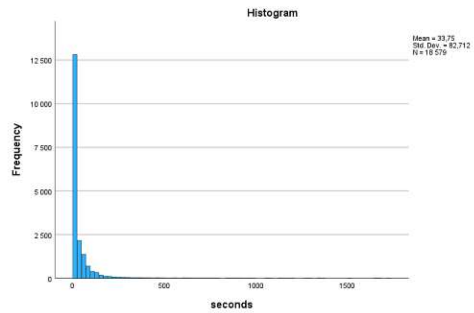

(e) Up to 1 minute.

Figure A.7: Leisure-time: Duration Histograms.

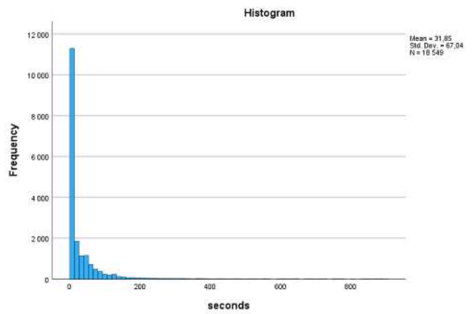
## A.7 Work-time Histograms



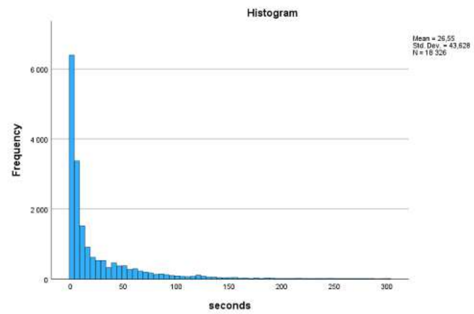

(a) Up to 1 hour.



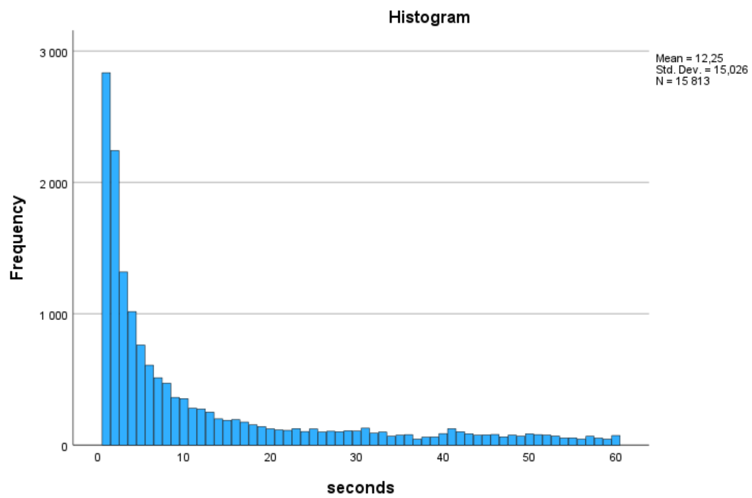

(b) Up to 30 minutes.




(c) Up to 15 minutes.




(d) Up to 5 minutes.




(e) Up to 1 minute.

Figure A.8: Work-time: Duration Histograms.

## A.8 Stress Levels Scale

These are the questions asked at the survey regarding stress written in the original language (German):

Gestern ... fühlte ich mich gestresst.
Gestern bei der Arbeit ... fühlte ich mich gestresst.

1. stimme überhaupt nicht zu
2. stimme überwiegend nicht zu
3. stimme eher nicht zu
4. stimme teilweise zu
5. stimme eher zu
6. stimme überwiegend zu
7. stimme voll und ganz zu

Translation to English:

I ... that I felt stressed yesterday.
I ... that I felt stressed at work yesterday.

1. do not agree at all
2. mostly disagree
3. rather disagree
4. partially agree
5. rather agree
6. mostly agree
7. totally agree

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# Bibliography


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