Universität Zürich[UZH]

Department of Geography

Lighting the way: Ambient Light’s influence on Mobile Map App Usage

GEO 511 Master's Thesis

Author: Choi Yeung Lo, 22-737-209

Supervised by: Dr. Tumasch Reichenbacher, Donatella Zingaro

Faculty representative: Prof. Dr. Sara Irina Fabrikant

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Abstract

Mobile map applications have become ubiquitous in the 21st century, supporting daily needs from commuting to travel and navigation need. Understanding how contextual factors influence interactions with mobile map apps is crucial for improving user experience. While prior research has explored how other elements, like motion or sense of direction, affect map app usage, the role of ambient light has received less attention, despite its known impact on visibility, perception and cognition (Song & Yamada, 2019; Tigwell et al., 2018).

This thesis examines how ambient light influences mobile map app usage by analysing tappigraphy data collected from the MapOnTap project, combining ambient light and GPS data obtained from smartphone sensors in a privacy-conscious, unobtrusive manner. Tappigraphy, a method adapted from neuroscience, captures users' touchscreen interactions passively, allowing for a naturalistic understanding of behaviour.

As a highly dynamic factor, ambient light varies by weather, time of day, physical environment, and even phone positioning. To account for these variables, a lightweight indoor-outdoor detection model was developed by combining GPS coordinates with light sensor data. This enabled a contextualised analysis that considered both temporal and spatial dimensions of light exposure.

Findings suggest that there is less general phone usage but more map app usage proportion in strong light situation, possibly indicating that users use mobile map more often in outdoors. On the other hand, it found that large variation in ambient light associate with reduced map app usage and slower tapping speed, visual discomfort or situational impairments like screen glare might explain such patterns. It also noted that ambient light alone was not a strong indicator of environment detection, but with combining it with other context data, it can still serve as a proxy to distinguish environmental states in a lightweight algorithm.

This study demonstrate how minimal, privacy-preserving data can be leveraged to analysed mobile map usage and provide insights into how users engage with mobile maps under different environmental conditions. It highlights the importance of including ambient light as a contextual factor in mobile app design and suggests that lightweight, privacy-conscious methods can offer valuable insight into real-world user experience. It is expected to contribute to research in Human-Computer Interaction by promoting more adaptive and environmentally aware design for map applications.

Keywords: *Map App usage, User Context, Ambient Light, Tappigraphy, Lighting Conditions, Indoor Outdoor Detection, Mobile Applications*

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List of Acronyms

DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DKL	Derrington-Krauskopf-Lennie
EMA	Ecological Momentary Assessment
GPS	Global Positioning System
HCI	Human Computer Interaction
HDR	High Dynamic Range
IMU	Inertial measurement unit
LBS	Location-based services
MOT	MapOnTap
OSM	OpenStreetMap
UZH	University of Zurich
UX	User Experience
VGI	Volunteered Geographic Information

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1 Introduction

1.1 Motivation

Mobile map applications have become an integral part of our daily lives, providing essential services such as navigation, travel support, and transportation assistance. As the use of mobile maps becomes increasingly ubiquitous, it is crucial to understand how users interact with these applications in different real-world conditions. Despite the widespread adoption of mobile map apps, gaining a comprehensive understanding of user behaviour across different contexts remains challenging (Zingaro et al., 2023). Previous research has shown that environmental factors such as cold temperatures, physical encumbrances, movement, and ambient noise can disrupt smartphone interactions (Sarsenbayeva et al., 2019). These disruptions are closely tied to the broader context in which mobile maps are used, which can be categorised based on the user's activity, task, physical environment, time of use, prior experience, and other human factors (Bartling et al., 2021).

Understanding the context of users is essential for designing effective context-aware mobile applications. Human-Computer Interaction (HCI) designers and User Experience (UX) consultants analyse the specific contexts in which mobile users operate, considering factors such as the where, when, why, and the conditions or constraints under which users engage with mobile content (Interaction Design Foundation, 2022). A thorough understanding of the user's contexts enables the development of context-aware applications and thus deliver more seamless and enhanced user experiences. "Context-awareness capability refers to the idea that devices or systems can react based on their environment, but also reason based on the user's current situation (Perera et al., 2014; Carrera-Rivera et al., 2022)". For instance, applications tailored to visually impaired users exemplify how contextual understanding can drive design innovation. The Seeing Eye GPS app integrates fully accessible turn-by-turn navigation features, specifically highlighting routes, points of interest, and locations to cater to this audience's needs (Interaction Design Foundation, 2022). Another app, Evelity, provides indoor wayfinding assistance for users with various disabilities, enabling them to navigate indoor spaces more effectively. Such designs underscore the importance of addressing users' unique circumstances to create inclusive and functional digital solutions.

Among a wide range of environmental contextual factors, this thesis aims to understand how ambient light affects mobile map app usage. Not only does light affect the brightness of our surroundings, but previous research has shown that it also influences cognitive processes such as perception, decision-making (Song & Yamada, 2019), memory (Oliver et al., 2023; Shang et al., 2021), and psychosocial responses (Casciani, 2020), while light is also a form of situational visual impairment which may raise safety concerns especially for drivers (Johananoff, 2024; RAC, 2025; Tigwell et al., 2018). The cognitive impact of light is out of the research scope of this thesis but the findings might provide some insights to cognitive field in future research.

Ambient light is a highly dynamic variable which varies depends on weather, time of day, and physical environment. To comprehensively assess its influence on map app usage, this study classified ambient light based on three dimensions: illuminance (lx), temporal differences (time of day), and spatial context (indoor vs. outdoor). However, light intensity values can overlap between settings, for example, 50 lx might occur on a dim street at night or in a bedroom; 500 lx may represent an office or sunset outdoors. Additionally, during daily mobile use, sensor readings may be affected by factors such as the phone being in a pocket, placed face down, or positioned near a window, leading to contextual ambiguity. To address these challenges and enrich the interpretation of ambient light data, a lightweight method was introduced to infer indoor and outdoor environments by combining ambient light and GPS coordinates. This allowed for a more nuanced analysis of how lighting conditions across different environments affect mobile map app usage.

Although previous studies have shown that visual impairment due to specific situations can make general mobile interactions more complex, such as Sarsenbayeva et al. (2019), no study has specifically explored how ambient light influence on mobile map usage. To fill this research gap, my thesis aims to deploy a recently novel technology to collect map app interactions that focuses solely on touch events on the smartphone, namely, tappigraphy (Balerna et al., 2018).

Unlike many previous studies of mobile map interactions, which are often conducted in controlled laboratory environments, tappigraphy offers a novel approach to studying user behaviour in natural, real-world conditions. Traditionally, small-scale user studies carried out in cartography and location-based services (LBS) research are limited to controlled lab settings. In contrast, tappigraphy allows for large-scale, remote, and in-situ data collection (Reichenbacher et al., 2022). In particular, my thesis uses tappigraphy data collected as part of the *MapOnTap* project on going to the geography department of the University of Zurich run by a PhD Student at GIVA group (see Zingaro et al., 2024).

This method involves unobtrusively and continuously recording touchscreen interactions in users' everyday contexts. By capturing detailed, ecologically valid data over long periods of time, tappigraphy provides unique insights into human-system interactions in real-world settings. It is widely used in neuroscience to analyse behavioural patterns and offers a powerful tool for studying mobile app usage in a way that reflects authentic user experiences (Zingaro & Reichenbacher, 2022). The *MapOnTap* project uses this technique to collect rich data in the wild, providing a richer understanding of how mobile maps are used in different everyday scenarios.

Understanding the context of mobile usage is essential for designing user experiences that are intuitive, accessible, and aligned with real-world needs, thereby enhancing usability and engagement (Interaction Design Foundation, 2022). This thesis aims to explore how contextual factors, such as ambient light, influence mobile map usage through the innovative integration of tappigraphy data with additional mobile data (e.g., light sensor and GPS module). The findings aim to provide insights into improving context-aware mobile design, enabling mobile maps to adapt dynamically to changing usage conditions. This approach aims to ensure that user interfaces respond effectively to environmental changes (Bartling et al., 2021), improving both usability and safety and ultimately promoting mobile maps that are more user-friendly and accessible in diverse real-world scenarios.

1.2 Research Questions

The objective of this thesis is to utilize data from the MapOnTap (MoT) project to develop a deeper understanding of user behavioural patterns associated with mobile map app usage under varying lighting conditions.

Given that ambient light is highly dynamic, shaped by factors such as weather, time of day, and environmental settings (see Subsection 2.1), this study aims to enrich our understanding by analysing map app usage through different light clusters and time-of-day comparisons. To further investigate the role of environmental context, this research will also explore map app usage in indoor versus outdoor environments.

Following the objective, the research questions of this master thesis are:

1. How can we leverage the taps, light, and GPS data to help distinguish between indoor and outdoor mobile map app usage?

   Hypothesis: Even without employing complex computational methods or additional enriched data sources, ambient light data in combination with GPS coordinates information can form a lightweight model for identifying indoor and outdoor usage, especially when supported by volunteered geographic information systems (VGIS).

2. Can tappigraphy, combined with light sensor data, be used to understand how the variation of ambient light influences mobile map app usage?

   Hypothesis: Map app usage is hypothesized to be more frequent in brighter environments, which may correspond to outdoor settings where navigation is more commonly required. Additionally, usage patterns are expected to peak during daylight hours, particularly on weekends when users are more likely to engage in travel or outdoor activities.

2 Background and Related Works

This chapter review the existing literature relevant to this thesis. The review starts with the foundation knowledge of illuminance and light in section 2.1. Subsequently, section 2.2 will review the key concepts of context of mobile map application usage, and how ambient light as a contextual factor influences Human-Computer-Interaction (HCI) and map usage. Followed by section 2.3 to introduce tappigraphy which is the methodological approach of this thesis. Lastly, the detection method of indoor and outdoor environment would be reviewed in section 2.4.

2.1 Fundamentals of Light

Light is a form of electromagnetic radiation that spans a vast spectrum, ranging from cosmic rays with wavelengths in the femtometer range to radio waves that extend up to kilometers in length (Boyce, 2014). The human eye perceives light within the visible spectrum, which ranges from wavelengths of 380 and 780 nanometers, distinguishing it from the rest of the electromagnetic spectrum (Atchison, 2023). Luminous flux refers to total amount of visible light emitted by a source, measured in lumens (lm). The higher lumen is, the more intense the light output. Luminous flux remains constant regardless of distance. Illuminance is the total luminous flux falling on a surface. It shows the luminous intensity over the unit area. The international system of unit of illuminance is lux (lx). It is defined mathematically as: Illuminance (Lux) = Lumens (lm) / area(m^2) where area is the illuminated area of the light source. Illuminance varies with distances. The farther the surface area away from the source, the larger the area would be, and hence the illuminance is smaller, while the luminous flux remains the same. For example, as shown on Figure 1, a 100-lumen light source illuminating a 1 m^2 surface results in 100 lux. If the same light source spreads over up 10 m^2, the illuminance drops to only 10 lux. Apart from distance, the beam angle also plays a crucial role in determining illuminance. Smaller beam angles produce higher illuminance as the light is more concentrated. Refer to the demonstration in Figure 1, with the same distance to the lighting source, a 100-lumen light source with a narrow beam angle illuminates only 1 m^2; in contrast, with a wider beam angle, the same 100-lumen light source illuminates 10 m^2, reducing the illuminance to just 10 lux.

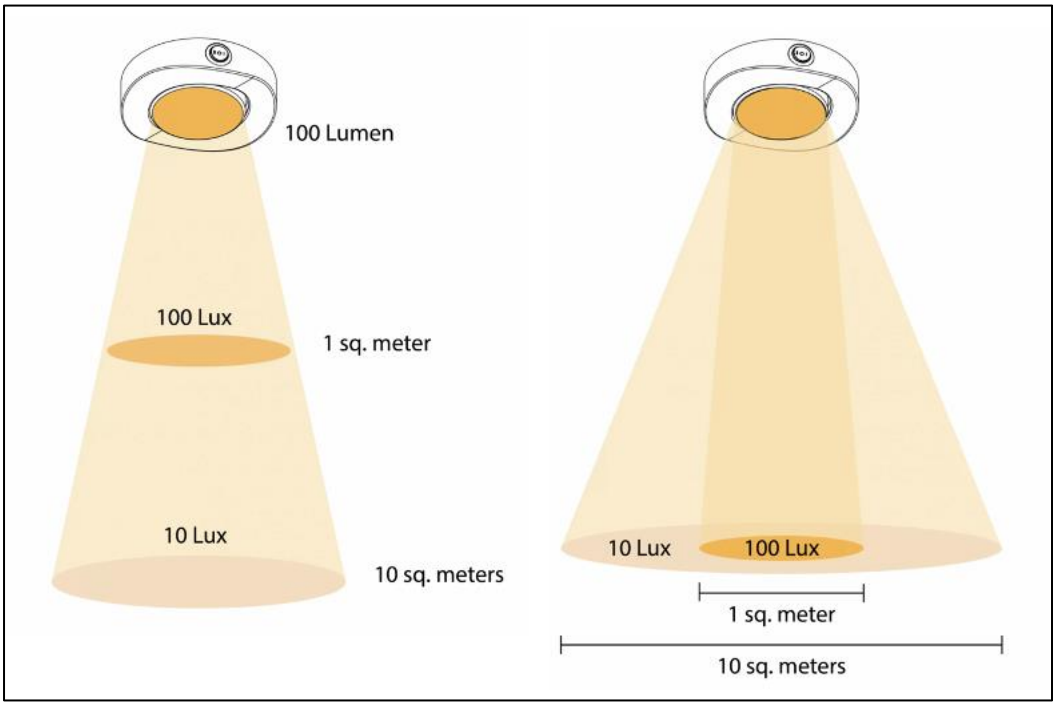


Figure 1. Distance and beam angle effects on illuminance (Source: Adapted from Yih Sean Enterprise Co, 2025)

Light intensity varies dynamically across different environment, depending on time of the day, season, weather conditions, and whether the settings is indoors or outdoors. During daytime, the sun is the dominant light source in outdoors (Xu et al., 2014). Sunlight and moonlight are the natural light sources, with illuminance ranging from as low as 0.0001 (Kyba et al., 2017) to as high as 105,527 lux (NOAO, 2015). While in indoors, artificial lighting such as fluorescent lamps, light-emitting diodes (LEDs), incandescent bulbs, are the primary lightening sources (Z. Wang et al., 2022). Unlike the natural lighting, artificial electric lighting typically provides a more stable luminance. Since light intensity varies fluctuates based on different factors such as environment conditions, distance from light sources, and beam angle, determining whether an individual is indoors or outdoors based solely on ambient light can be challenging. Table 1 presents common light intensity values for various settings (NOAO, 2015; Aslam et al., 2020; Bhandary et al., 2021; Shishegar et al., 2021), while Figure 2 illustrates how light levels fluctuate throughout the day under different conditions (Knoop et al., 2020). From Figure 2, we can observe that the indoor illuminance typically ranges from 500 lux in the evening to 1,500 lux under a clear sky. In contrast, outdoor illuminance spans from approximately 1,500 lux on overcast days to 30,000 lux under bright sunlight. As shown on Table 1, the light intensity is overlapped in some conditions. For example, am illuminance level between 100 to 200 lux may be observed in both dimly lit open space on very dark days and in indoor residential rooms. Similarly, an illuminance of 500 lux may correspond to indoor educational facilities or shaded outdoor areas surrounded by multiple buildings. Nevertheless, research suggests that indoor environments tend to peak around 1000 lux, while outdoor environments generally exhibit higher light intensity, even on overcast days (Daugaard et al., 2019; Aslam et al., 2020).

Scientists use climate-based daylight modelling to assess the annual impact of daylight availability (Mardaljevic et al., 2009). One of the daylight metrics is useful daylight illuminance (Nabil and Mardaljevic, 2005) which is defined as the percentage of annual operating hours of a space for which the illuminance provided by daylight is within the range of 100-2000 lx. It considered that artificial lighting will be the dominant light source for illuminance below 100 lx, and it is likely to associated with glare for illuminance above 2000 lx (Boyce, 2014), potentially causing visual discomfort.

To gain a better understanding of ambient light conditions, I recorded the light levels at several locations, ranging from outdoor to indoor, around the UZH Irchel campus using an app called Luxmeter. The measurements are shown in Table 2 (sunny weather), Table 3 (rainy days) and Table 4 (indoor environments). It can be observed that the light intensity outdoors generally exceeds 1200 lx. Glare is also experienced under strong light conditions above 2000 lx, making it difficult to view the readings on a smartphone screen. Furthermore, while light intensity is lower on rainy and cloudy days, it still differs profoundly from indoor lighting. Table 4 compares ambient light levels in indoor buildings at different times. The daytime measurement was taken around 2PM on a sunny day while the nighttime measurement was taken at around 7PM on a cloudy day. Both records were taken in April. It is to note that for some locations without windows, such as the study room in Y25-J93, light intensity remains constant over time.

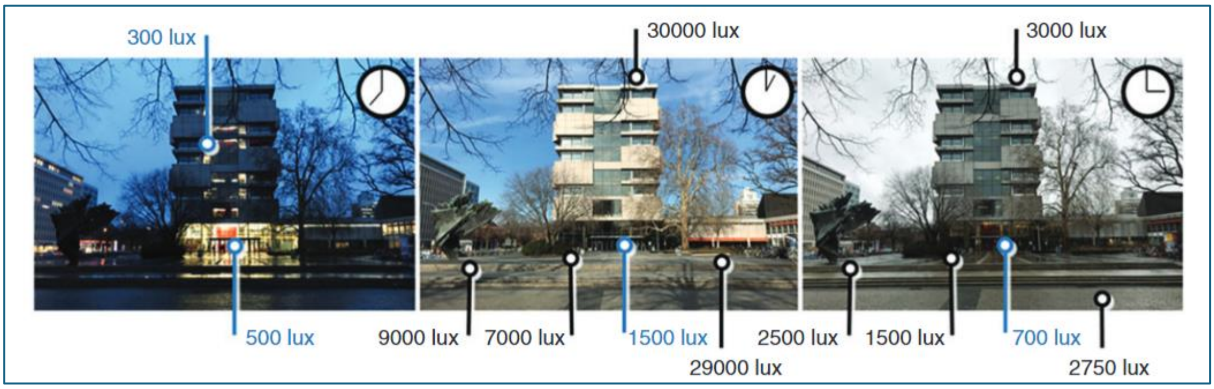


Figure 2. Range of approximate illuminance levels of indoors (blue colour) and outdoors (black colour) in example of situations during winter time in Berlin, Germany (Left: evening; Middle: clear sky condition; Right: overcast sky condition in afternoon) (Source: Knoop et al., 2020)

Environment/ Condition:	Light (lux):
Day:	
Sunlight	107,527
Overcast Day	1,075
Very Dark Day	107
Night:	
Twilight	10.8
Deep Twilight	1.08
Full Moon	0.108
Overcast Night	0.0001
Weather:	
Rainy	10,000
Cloudy	20,000
Sunny	50,000
Indoors:	
Living rooms	100-150
Bedrooms	60-100
Kitchens	250-300
Bathrooms	150-300
Libraries	500
Classrooms	300-500
Laboratories	750-1000
Supermarket	1000
Offices	300-500
Room with multiple large windows	2,650 (Range from 350 – 28,500)
Room with multiple artificial lights	290 (Range from 200 - 510)
Room with single artificial light	14 (Range from 9 - 116)
Outdoors:	
Open Playground	14,350 (Range from 1,120 - 93,500)
Under the translucent artificial shade	13,300 (Range from 910 - 80,200)
Within 3 buildings	500 (Range from 56 – 9,080)
Within 4 buildings	17 (Range from 4 - 102)
Under a big tree	1,700 (Range from 96 - 15,000)
Under canopy	178 (Range from 21-2,600)
Under a porch facing south	2,200 (Range from 212 - 20,500)
Under a porch facing east	1,685 (Range from 40-36,400)

Table 1. Ambient Light Range for different settings

	
Irchel Lake: 36,000 lx	Irchel Park: 11,200 lx
	
Near the rock statue (Direct sunlight): 32,000 lx	Near the rock statue (Under Shade): 5,700 lx
	
Close the the entrance of Y14 (Outdoor): 230 lx	Close the the entrance of Y14 (Indoor): 110 lx

Table 2. Ambient light measurement in UZH Irchel Campus in sunny days

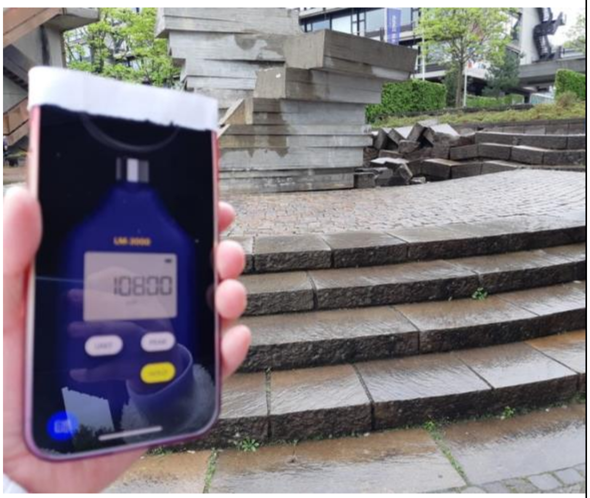
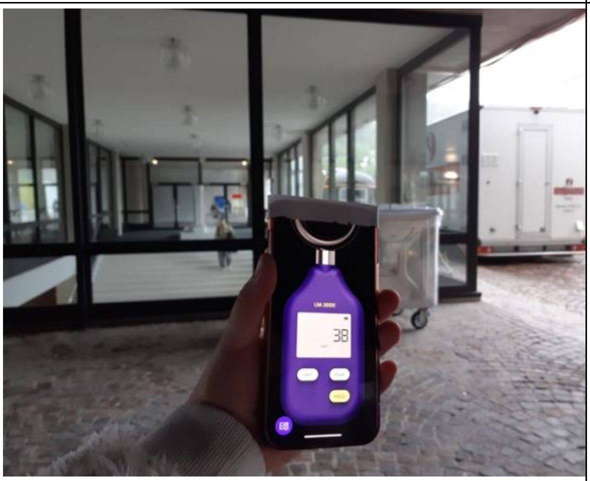
	
Irchel Lake: 7,600 lx	Open area near the Science Pavilion UZH: 14,300 lx
	
Near the rock statue: 10,800 lx	Near the rock statue (further than the previous spot): 6,100 lx
	
Close the the entrance of Y14 (Outdoor): 38 lx	Close the the entrance of Y14 (Indoor): 86 lx

Table 3. Ambient light measurement in UZH Irchel Campus in rainy days

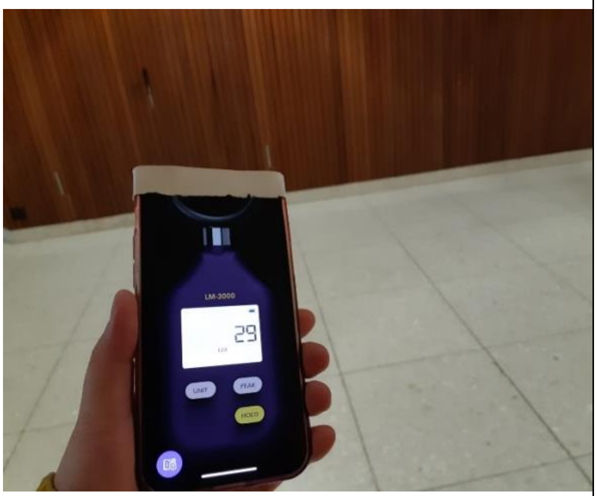
	
(Day) Front area of staircase in Y25: 500 lx	(Night) Front area of staircase in Y25: 58 lx
	
(Day) Close to the entrance of Y25: 550 lx	(Night) Close to the entrance of Y25: 69 lx
	
Corridor at Y04: 29 lx	Study room Y25-J-93 (no window): 300 lx

Table 4. Ambient light measurement in UZH Irchel Campus indoors - both daytime & nighttime

2.2 Ambient light as a contextual factor of map app usage

In today's increasingly mobile digital society, understanding and responding to context has become fundamental for creating effective user experiences. As mentioned by Reichenbacher and Bartling (2023), "Digital transformation is inexorably penetrating and impacting the daily life of citizen". The rapid advancement of mobile technology and widespread adoption of smartphones has transformed how people interact with digital information, making it essential to consider the diverse situations in which these interactions occur (Reichenbacher & Bartling, 2023). Figure 3 illustrates how different contextual factors could affect user's mobile and digital behaviour.

Context in mobile computing encompasses multiple interconnected dimensions that influence user interaction. Research has identified several key categories of contextual factors that shape mobile device usage. Physical or environmental factors include location, weather conditions, and ambient light levels, which can significantly impact visibility and interface usability (Bartling et al., 2022). Temporal factors comprise time of day, season, and situational urgency, all of which affect user behaviour and device interaction patterns. User-specific factors encompass individual differences such as spatial abilities, cognitive states, and experience levels with technology. Additionally, social and cultural contexts play crucial roles, as they influence how users interpret and interact with interface elements, including colour schemes and icon symbolizations (Bartling et al., 2022).

The influence of the lighting environment on map use has been a topic of interest among cartographers. Raubal and Panov (2009) and Weninger (2012) suggested that map symbols should be adjusted based on the time of day or season to enhance usability. To mitigate visibility challenges caused by different lighting conditions, Schilling et al. (2005) and Zhang et al. (2009) proposed that interfaces should adapt to varying light levels, such as by modifying map symbol colours or label sizes (Sarjakoski & Nivala, 2005). Furthermore, Bartling et al. (2022) emphasized that map design should be tailored to the surrounding environment to prevent excessive cognitive load. Despite these recommendations, there is still a lack of empirical research examining the usability of maps across different lighting conditions

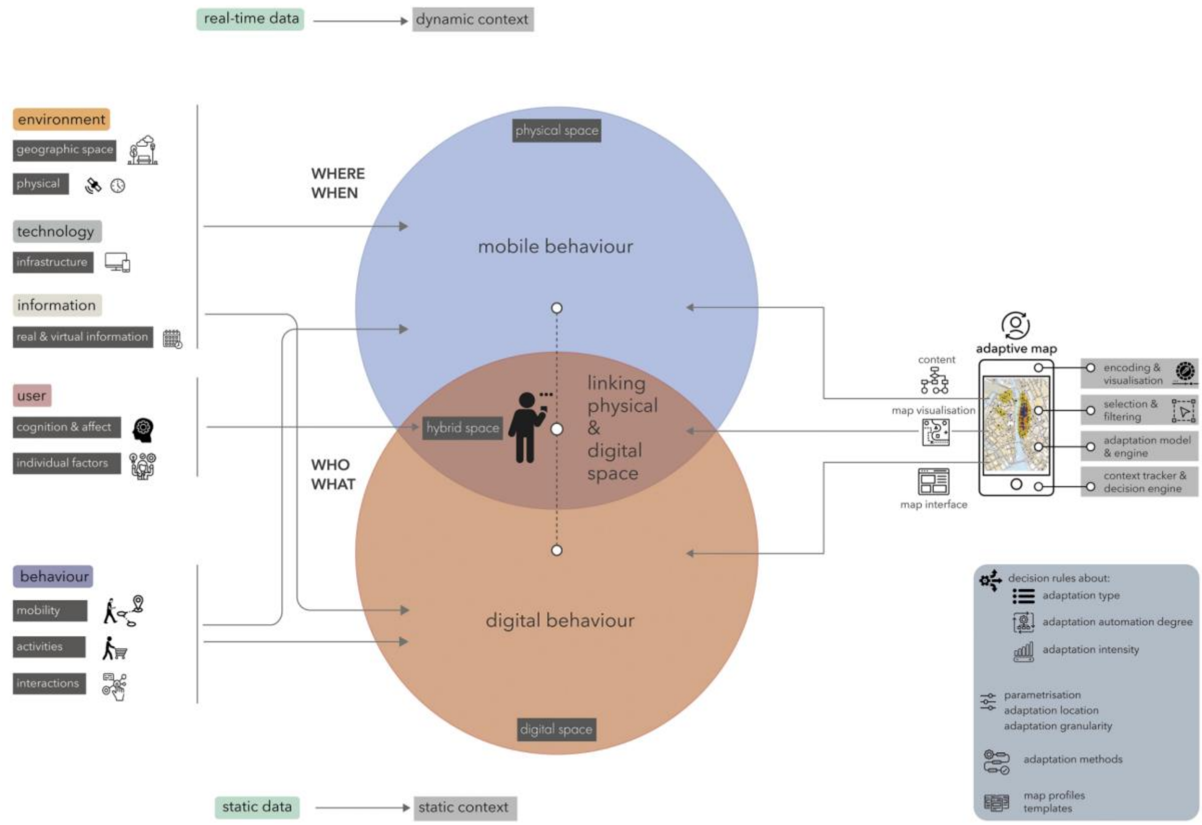


Figure 3. Conceptual model for mobile map use and adaptivity (Source: Reichenbacher & Bartling, 2023)

Previous research has studied the effect of context to the mobile applications. Verkasalo (2007) explored the usage patterns of mobile services and how they vary based on the user's context: at home, in the office, and "on the move." They found that multimedia service apps, such as entertainment-related and music player apps, had higher usage when users were mobile, and less usage in stationary states where alternative devices might be available. This finding provides insight that analysing contextual patterns in mobile services can lead to better service design and a deeper understanding of user behaviour.

Kronbauer and Santos (2014) examined how various contextual factors affect mobile application usability by evaluating participants' accuracy rates on assigned tasks across three different mobile applications. They focused on interaction contexts, including screen resolution (low/ medium/ high) and phone size (small/ medium/ large), along with environmental contexts including luminosity (low: lower than or equal 100 lux/ medium: 100 to 10,000 lux/ high: higher than 10,000 lux), user's movement (stationary/ walking/ motorized), and the position of the phone (vertical/ horizontal/ mixed). The study found that the highest error rates occurred under conditions of low resolution and small screen size, as well as in scenarios with extreme luminosity levels (either too low or too high) and when users were in motion. It demonstrated that users were more prone to make mistakes and took longer to complete tasks when the context changed, highlighting the significant impact of contextual factors on usability outcomes.

These studies demonstrated that contextual factors do have an impact on human-computer interaction.

Among a wide range of environmental contextual factors, this thesis aims to understand how ambient light affects mobile map app usage. Not only does light affect the brightness of our surroundings, but previous research has shown that it also influences cognitive processes such as perception, decision-making (Song & Yamada, 2019), memory (Oliver et al., 2023; Shang et al., 2021), and psychosocial responses (Casciani, 2020), while light is also a form of situational visual impairment which may raise safety concerns (Tigwell et al., 2018). The cognitive impact of light is out of the scope of this thesis. However, it provides some insights of how ambient light affect cognitive field in future research. Ambient light can influence visual attention subconsciously. It plays a crucial role in implicit guidance systems. A pilot study found that even minimal changes in lighting conditions can significantly affect user behaviour in indoor environments, which infers that indoor navigation might be influenced by ambient light (Tscharn et al., 2016).

It is worth noting that ambient light might cause safety concerns, especially while driving. A study conducted a survey and categorised 15 ambient light positions inside a car. The result showed that the high preference positions are either centre screen surround, armrest, or centre screen bottom; Medium preference positions included the centre screen top, audio, cup holder, roof, air conditioner vents, and floorboard; Low preference positions were locations such as the A-pillar, rear view mirror and steering wheel (Liu et al., 2023). Those lowest preference positions had the potential to interfere with driving safety. The findings stressed that ambient light position is closely related to safety concerns. In fact, in the United State, there are over 9,000 vehicle accidents each year are attributed to sun glare (Johananoff, 2024). Sun glare occurs due to a sudden change in sunlight and tends to peak during rush hours (7 – 9 a.m. and 5 – 7 p.m.), making it particularly dangerous. Moreover, glare is not only a daytime issue, headlights in vehicle can also causes glare at night. Another survey conducted in the United Kingdom revealed that 25% of drivers who believed vehicles headlights are too bright prefer to drive less at night, and some had even stopped driving completely due to the brightness of other vehicle s’ headlights (RAC, 2025). Nowadays, mobile map app usage during driving is very common (Lee & Cheng, 2008; Wang et al., 2015; Knapper, 2018) and most cars are equipped with interior ambient lighting (Liu et al., 2023), increasing the likelihood that drivers will use mobile maps during driving. Therefore, I emphasise that there is a need to examine how ambient light impact on map app usage under different lighting condition.

Situational visual impairments (SVIs), such as those caused by bright ambient light, can significantly disrupt mobile device usage (Tigwell et al., 2018). Research has shown that users frequently encounter bright-light SVIs during common mobile tasks like texting or media consumption, often leading to frustration. Complementary findings from controlled experiments demonstrate that lighting conditions, including dim light or wearing sunglasses, impair performance in visual tasks such as target acquisition and recall, although some activities like text entry appear more resilient (Sarsenbayeva et al., 2019). Together, these studies underscore the sensitivity of mobile interactions to varying ambient light conditions and the need for adaptive design.

The above studies are about the impact of ambient light on general mobile app usage, but not explicitly for map app usage. In terms of the relation of ambient light and map app behaviour, some previous research has studied this relation in experimental settings. For example, Qiao and Wu (2023) investigated the usability of web map on light-mode and dark-mode in bright (200 lux, from 10am to 4pm) and dark environment (0 lux, from 8pm to 11pm) via eye-tracking experiments, in terms of effectiveness, efficiency, and cognitive load. The result found that light-during-the-day had the best performance in most scenarios, followed by dark-at-night performance while dark-during-the-day had the worst performance in most cases. This finding suggests that aligning the map appearance with the lighting environment is critical for better communication of web maps where possible reasons might be related to colour differences in different modes affect the visual perception of map features, as well as the colour boost visual pleasure (Qiao & Wu, 2023). This research provided some insight to my thesis and may help to evaluate the relationship between light range interval and map app usage variables.

These former studies highlight the important role of lighting conditions in mobile interactions, particularly in tasks that require precise touch input, such as map navigation. While Tigwell et al. (2018) approached the problem through questionnaires and ecological momentary assessments, Sarsenbayeva et al. (2019) & Qiao & Wu (2023) conducted experiments in a laboratory setting to provide controlled, measurable insights into the effects of lighting on user performance. These studies underscore the need for mobile interfaces that adapt to varying lighting conditions. However, the stable lighting in laboratory settings does not reflect the inherently dynamic nature ambient. Laboratory environments typically represent indoor conditions, where artificial lighting is the dominant source. My thesis will build on these findings using tappigraphy data collected in real-world conditions, capturing a broader range of lighting scenarios and mobile map app usage in situ. This approach overcomes the limitations of questionnaires and lab experiments by providing continuous data through ambient light sensors and touchscreen interaction logs. By investigating the impact of ambient light on mobile map usage in real time, my research aims to provide some insights on how adaptive design can address the challenges posed by fluctuating lighting conditions and enhance the user experience across diverse environments.

2.3 Tappigraphy – a novel approach borrowed from cognitive science

Tappigraphy is a methodology that unobtrusively and continuously records every touch event, in other word, *tap*, on a smartphone screen, typically capturing the timestamp and associated app, without logging exact screen coordinates or personal identifiers (Reichenbacher et al., 2022). It is considered as one form of digital phenotyping, which has been defined as the prediction of psychological traits and state from digital variables obtained from smartphone data logs (Montag & Quintana, 2023). Figure 4 presents examples of how data from built-in smartphone sensors, such as the ambient light sensor, GPS, accelerometer and microphone, can be used to measure various behaviours and infer psychological and contextual phenotypes, including mood, social behaviour, sleep disturbances and activity levels (Montag & Quintana, 2023).

Unlike traditional empirical methods used in location-based services (LBS) and the GIScience field, such as human map display, interaction logging, automatic map screen recording, mobile eye tracking, think-aloud protocols, or digital surveys, tappigraphy provides highly detailed, ecologically valid data as people naturally use their devices (Reichenbacher et al., 2022). It is intentionally minimalist to protect user privacy, ensuring that no sensitive information like content, demographics, or system data is recorded (Zingaro et al., 2023). This approach enables continuous capture of behaviour in real-world settings over extended periods and across a large, anonymous participant base, all without researcher intervention or direct participant contact, while being more cost-effective and requiring less workforce than traditional empirical studies (Reichenbacher et al., 2022). Figure 5 illustrates the structure of tappigraphy, where participants, even the same individual, may exhibit varying tap speeds, tap counts and session durations over time (Reichenbacher et al., 2022). Rather than direct observation of self-report methodology, tappigraphy provides a rich and fine-grained temporal sequence of interactions, supporting large-scale, remote, and real-world assessments "in-the-wild" over periods ranging from days to months (Reichenbacher et al., 2022; Zingaro et al., 2024).

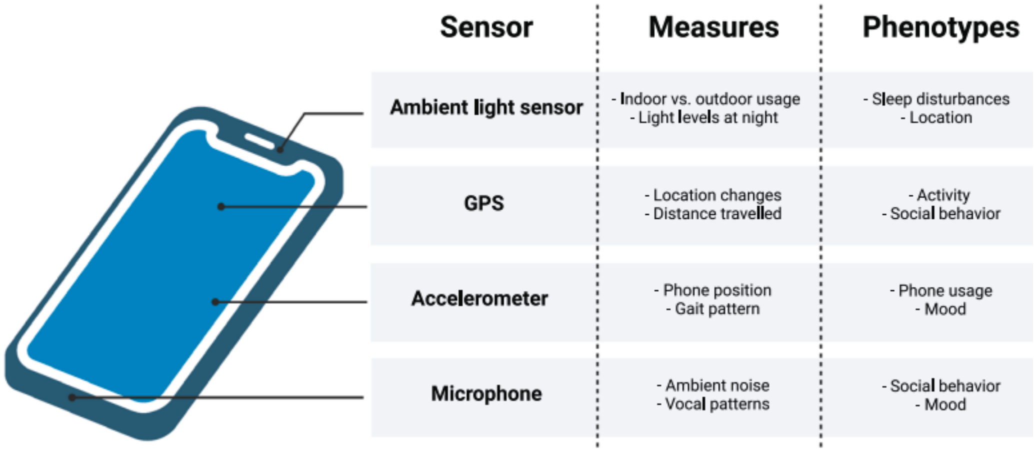


Figure 4. Application examples of phenotypes from different smartphone sensors (Source: Montag & Quintana, 2023)

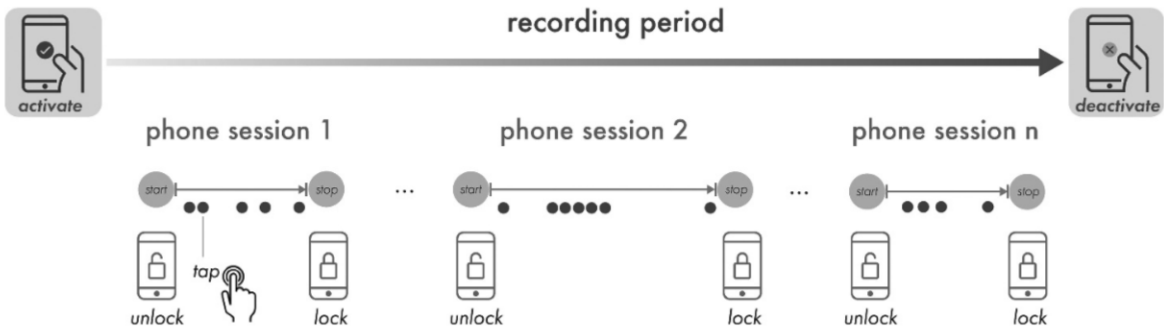


Figure 5. Structure of tappigraphy data where the black dots represent individual taps within the same phone sessions (Source: Reichenbacher et al., 2022)

Tappigraphy was originated in cognitive and behavioural neuroscience (Borger et al., 2019). It has been applied to examine the relationship between touch patterns and various cognitive or health related processes. For examples, it could infer sleep patterns as late-night tapping suggests wakefulness (Corbyn, 2021), and the timing and frequency of taps can be used as proxies for sleep-wake cycles (Borger et al., 2019); It could help on assessing cognitive performance as fast and closed spaced taps may reflect reaction times, which are relevant for gauging mental performance and alertness (Zingaro et al., 2024); Sensorimotor analysis also associated tapping patterns with social interaction in motor function and cognitive processing speed (Balerna & Ghosh, 2018; Zingaro et al., 2024). Other health disease and mental health disease are also examined with digital phenotyping with tappigraphy as foundation. Subtle changes in smartphone tappigraphy might infer abnormalities in brainwaves for people with epileptic seizures; while neurological health issues like depression, schizophrenia, bipolar disorder and autism might be correlate with tapping behaviour (Corbyn, 2021).

Recently, tappigraphy has been adopted by Geographic Information Science (GIScience) and Location-Based service (LBS) as a tool for understanding real-world mobile map app use. It has been used as an ecological momentary assessment (EMA) method to continuously document how, when, and where individuals use map apps in their daily lives (Reichenbacher et al., 2022; Zingaro & Reichenbacher, 2022). It has been adapted to analyses of individual and group patterns, and spatial context and distance-based behaviours. For instance, Zingaro et al. (2024) have examined the association between sense of direction and spatial anxiety in individual's map app usage; Zingaro & Reichenbacher (2022) explored if and how map app usage varied based on the user's distance from home; Zingaro et al. (2024) studied active and passive in-app usage behaviour by analysing the users' tapping rates; in the Master's thesis of Signer Del Cid (2024), behaviour patterns related to user mobility (stationary and non-stationary movement) were examined.

In this thesis, I leverage tappigraphy data collected from the MapOnTap project to investigate how ambient light influences mobile map interactions. This methodology is particularly valuable as it allows for the capture of dynamic ambient light intensity through continuous and ecological data collection in everyday environments without compromising user behaviour or privacy. This unique approach offers novel insights into how lighting conditions, time of the day and environmental states.

Cognitive load & Tappigraphy

Cognitive load refers to the mental effort required for users to process information and make decisions (Albers, 2011; Block et al., 2010; Griffin et al., 2024; Martin & Bajcsy, 2011). In the context of map app design, managing cognitive load is crucial because mobile map users often operate in complex, dynamic environments such as walking outdoors or navigating on busy streets (Griffin et al., 2024). These contexts place extra demands on user's attention, memory, and decision-making abilities (Griffin et al., 2024). When cognitive load is high, it lowers task accuracy and hinders the comprehension and performance (Albers, 2011) making it difficult for one to accomplish their goals. Moreover, mobile devices have inherent constraints, like the small screen sizes and potential distractions from push notification. High cognitive load can negatively affect spatial learning and user engagement. A well-designed map app can help users efficiently allocate their attention between the app and their real-world context. By reducing extraneous cognitive load through good interface design such as simplifying visuals, providing adaptive content, and incorporating context-aware features, it enables users to make better and quicker decisions without experiencing cognitive overloaded (Griffin et al., 2024).

To measure cognitive load, there are traditionally three types of approaches: subjective measures, behavioural measures, and psychophysiological measures. For subjective approach, the most common method is the self-reported NASA Task Load Index, which is a multidimensional scale of perceived workload consisting of six aspects rated on a seven-point scale (Grimes & Valacich, 2015; Albers, 2011). Behavioural measures may include the analysis of participant' s gait and handwriting, and typing (Martin & Bajcsy, 2011). Physiological assessment techniques, including eye-tracking and pupillometry (which measures gaze pattern and pupil dilation), electroencephalography (EEG), heart rate monitoring, and functional magnetic resonance imaging (fMRI), have been utilized in studies focused on map usage or navigation (Grimes & Valacich, 2015; Qiao & Wu, 2023; Griffin et al., 2024). There are also indirect measures, such as duration judgements (Block et al., 2009) which are based on the theory that when people work on a challenging or attention-demanding task, time seems to pass more quickly, whereas time appears to pass more slowly during an easier task. Each of these methods offers distinct advantages and limitations. For instance, self-report measures can be biased by personal perception, while physiological assessments might disrupt the natural interaction with the equipment, thereby preventing participants from fully engaging in their primary tasks during the experiments (Grimes & Valacich, 2015). Additionally, the cost of equipment is expensive, and specialised training is required before applying it to participants (Albers, 2011). Research has suggested that tapping techniques can unobtrusively detect the cognitive load of participants (Albers, 2011; Grimes & Valacich, 2015).

Although there has not yet been research on using tappigraphy on smartphone to measure cognitive load, tapping tasks as a secondary cognitive has a long history of use in psychology and human-computation interaction studies (Albers, 2011). The tapping task is a simple method of imposing a secondary load on a user. Albers (2011) examined how cognitive load theory applies to website design by using tapping test as a practical method of measuring cognitive load. In their experiment, participants were asked to tap their fingers on a desktop or a recorder key rhythmically while performing a trivial task on a specific website. This tapping task required cognitive resources to maintain a steady rhythm and served as a secondary load on participants. The results showed that the tapping rhythm remained constant for task which required less mental effort for web navigation and content interaction. However, a the websites became more informative and complex, leading the increase in usability issues, participant' s cognitive load also increased. Consequently, they tended to focus on the primary task and lost concentration on the tapping task, resulting in slower and less rhythmical tapping. Their study demonstrated that tapping task can be used as measures of cognitive load for usability purpose.

Different to Albers' s research, Grimes and Valacich (2015) investigated cognitive load using mouse movement behaviour as a direct measures. This research provides valuable insights for my thesis, particularly in linking tappigraphy (tap behaviour) and cognitive load. They recruited 68 participants for an experiment conducted on a web application, where the participants were required to complete three tasks that progressively demanded higher cognitive effort. Alongside the NASA task Load Index, the study recorded five metrics related to mouse dynamics technique, including: (1) total duration of the task,(2) mouse movement calculated by Euclidean distance, (3) mouse traveling speed, (4) number of direction changes, and (5) number of mouse clicks. The result indicated that participants under high cognitive load tend to spent more time on tasks, moved the mouse further, exhibited slower mouse movement and more direction changes. The hypothesis testing demonstrated significant differences in longer mouse distances and slower movements under higher cognitive load; The longer task duration and greater direction changes were only partially significant to high cognitive load. However, no significant results were found to suggest an increase in mouse clicks under high cognitive load conditions (Grimes & Valacich, 2015). While Grimes and Valacich's study focuses on mouse movement behaviour to measure cognitive load, my thesis analyses tap data on smartphones instead of mouse clicks or movements on web pages. Nevertheless, I will reference their findings to explore whether cognitive load can be inferred through mobile-specific metrics such as total tap counts per session, phone session duration, and tap speed under varying lighting conditions. Although technical constraints prevent the capture of metrics like inter-tap distance or directional changes, the available tap-based indicators still offer valuable behavioural insights into user' s cognitive engagement on map app usage.

2.4 Indoor & Outdoor environments detection

Since the advent of smartphones equipped with numerous built-in sensors, indoor-outdoor detection using smartphone data has become a popular research topic over the past decade due to its crucial role in positioning technologies and environmental change detection using multimodal smartphone sensors (Dastagir et al., 2024). Previous research has explored several indoor-outdoor detection strategies, mainly focusing on multi-sensor fusion and machine learning algorithms. The widespread adoption of smartphones equipped with various sensors and powerful processing capabilities has enabled more sophisticated approaches to context detection (Dastagir et al., 2024).

Multiple sensors and advanced detection methods to determine whether a user is in an indoor or outdoor environment. Traditional sensor-based approaches leverage several key smartphone components. The GPS module serves as a primary indicator, where signal availability and accuracy typically correlate with outdoor environments (Zhou et al., 2012). Light sensors play a crucial role by responding quickly to environmental changes, though they face challenges in distinguishing between semi-outdoor and outdoor scenes during daylight, or between dark outdoor spaces and indoor rooms with lights off (Xu et al., 2014; Ali et al., 2018). Magnetometer can detect variations in magnetic fields, which tend to be more stable outdoors and more variable indoors due to building materials and electronic devices (Radu et al., 2014; Xu et al., 2014; Zhou et al., 2012). Wi-Fi signal patterns and availability of access points, as well as cellular signals strength variations are also used as indicators of indoor and outdoor environments classifications (Zhou et al., 2012; Wang et al., 2016).

Recent research has focused on combining multiple sensors and implementing machine learning approaches to improve detection accuracy (Zhu et al., 2024). For instance, DeepIOD framework integrates IMU (inertial measurement unit) sensor data, GPS, and light sensors, using multiple deep neural network models and sensor modules to robustly predict the environment type with accuracy rate of 98-99% (Dastagir et al., 2024). This comprehensive approach has demonstrated remarkable accuracy rates ranging from 98 to 99% with transition time of less than 10 milliseconds (Dastagir et al., 2024); SenseIO system introduced a fine-grained indoor-outdoor detection by leveraging multiple sensors embedded in smartphones, which not only identifies whether a user is indoors or outdoors but also distinguishes between various environmental subtypes such as rural, urban, and complex places, and achieving over 92% accuracy (Ali et al., 2018); IODetector is an approach for environment (indoor, outdoor and semi-outdoor) detection integrating three primary lightweight sensors, including light sensors, magnetism sensors, and cell tower signals, with Hidden Markov Model (HMM). Their basic stateless version achieves 82% accuracy while the more sophisticated stateful version achieves over 88 % accuracy (Zhou et al., 2012).

Although the integration of different kinds of sensor data might provide satisfactory accuracy in context detection, there are some drawbacks of different sensors. For example, GPS modules consume substantial energy and can be unreliable indoors (Radu et al., 2014). Cellular signals require sufficient cell tower coverage and can vary significantly across different places (Zhou et al., 2012). Wi-Fi-based detection methods depend heavily on the availability and stability of access points (Zhou et al., 2012). Furthermore, using multiple sensors increases power consumption and computational complexity (Zhu et al., 2019). Some machine learning approaches require extensive training data or pre-knowledge of environments, limiting the practical applicability (Radu et al., 2014). Due to these technical limitation, as well as the data collection constraints of the MapOnTap Project, this thesis leverages a lightweight method that considers only time of day, ambient light, and GPS data (coordinate). This approach is adapted from Xu et al. (2014) work, who implemented a joint detection method relying primarily on ambient light, time and GPS modules. Since context detection was not the main focus during the MOT project's data collection, GPS modules data was not collected. Instead, coordinate data was collected when GPS sensor was activated and authorised by participants. Moreover, unlike the study of Xu et al. (2014), ground-truth data for indoor and outdoor environment was not collected in MOT project. To obtain spatial information, building footprints from OpenStreetMap (OSM) are utilised. My approach leverages time, ambient light intensity, and OSM building footprints to create a lightweight method that minimises the need for multiple sensor inputs or complex machine learning models. This aligns with the study's focus on context-based evaluation rather than achieving absolute accuracy. Such a lightweight approach also preserves participant privacy by minimising sensor accessibility. On the other hand, similar to study of Radu et al. (2014), this thesis considers only two basic states, indoor and outdoor environment, for context classification (Radu et al., 2014) rather than including subtypes, such as semi-indoor, semi-outdoor, light indoors, and deep indoors. This decision stems from two factors: these two basic states are the most relevant to context-aware applications, and there is considerable ambiguity in defining semi-outdoor or semi-indoor across different studies (Wang et al., 2016; Zhou et al., 2012).

OpenStreetMap as a tool of Volunteered Geographic Information

OSM is an open-source, collaborative project that creates and maintains a free editable map of the world. It is widely recognized as one of the most successful Volunteered Geographic Information (VGI) projects (Z. Wang & Niu, 2018). The project's primary output is not just the map itself, but rather the extensive data generated through volunteer contributions (Cantarero Navarro et al., 2020). Through its central database, OSM enables users worldwide to access, edit and download geographical data using three basic data types: nodes, ways, and relations, enriched by tags (key-value pairs) to describe real-world objects (Wang & Niu, 2018). Recent research has validated OSM's data quality, showing it provides sufficient completeness and correctness compared to proprietary solutions (Cantarero Navarro et al., 2020; Klipp et al., 2021; Z. Wang & Niu, 2018). OSM's most notable advantages include its wide range of application, continuous updates through community contributions, and extensive transportation features like roads, bus stops, and sidewalks (OpenStreetMap, 2025; Cantarero Navarro et al., 2020). Furthermore, OSM's infrastructure allows sharing maps between users, creating potential for robots and systems to share their maps with others.

Previous research had already studied indoor-outdoor detection by using the data and the building footprints from OSM. For instances, Li et al. (2023) utilized OSM building footprints complemented with points of interest (POIs) to learn region representations since buildings' shapes, spatial distributions, and properties have strong connections to different urban functions; Cantarero Navarro et al. (2020) proposed approaches for integrating indoor and outdoor spatial data to enhance navigation and spatial awareness by combining multiple geospatial standards through OSM, IndoorGML, and Open Location Code; Wang and Niu (2018) discusses how OSM data can be used to facilitate seamless route planning for pedestrian between indoor and outdoor environments, introducing a data model that extends OSM's existing capabilities by integrating indoor navigation information with the outdoor street network; Klipp et al (2021) demonstrated a practical application by utilizing OpenStreetMap to provide basic building information for tracking pedestrians, particularly individuals with dementia, in both outdoor and multi-level indoor environments. Their approach integrates a foot sensor for relative movement, GNSS for absolute positioning, and a barometer for height detection, all within a particle filter-based probabilistic framework. Even with minimal OSM building data, their system achieves sufficient accuracy for locating individuals inside unknown buildings (Klipp et al., 2021).

These studies collectively demonstrate that OSM's building footprints and associated data structures provide valuable spatial context for indoor-outdoor detection systems, offering both geometric reference points and semantic information that can enhance the accuracy and reliability of environment classification. This makes OSM a promising resources for my thesis for developing a sophisticated indoor-outdoor detection solution. I will take the building footprint from OSM as a physical characteristics. Despite the high accuracy of OSM, there are some possible limitations too. It is known that the indoor mapping quality solution primarily focus on human navigation rather than automated application (Grinberger et al., 2022; Naik et al., 2019). For some complex buildings with both surface and underground area, it may be challenging to identify whether it is indoor or outdoor solely from the data of OSM. Thus, in my thesis, apart from OSM, I would also consider ambient light as a factor for context detection. The light intensity threshold for distinguishing between indoors and outdoors in IODetector was at 2000 lux (Zhou et al, 2012). However, subsequent research has shown that some outdoor locations do not consistently record such high values throughout their routes (Radu et al., 2014). Additionally, light intensity varies significantly depending on weather conditions and environment (Table 1; Dastagir et al., 2024). Therefore, based on these findings, this thesis will use a more flexible threshold of 1200 lux for outdoor detection. The details of methodology would be further discussed in Section 3.6 Indoor/ Outdoor Environment Classification.

3 Data & Methods

This chapter outlines the methodological framework used in this thesis. It begins with the stages from data collection via the MapOnTap project, to data alignment, data pre-processing, data aggregation and data visualisation. The workflow of the thesis is illustrated on Figure 6.

All of the data pre-processing, analysis, and visualisation were conducted in Python 3 environment. The scripts were stored in Jupyter Notebook files and submitted to GitHub along with the thesis document.

An app category represented a group of apps that have similar features, functionality, and themes. The Google Play Store currently offered 33 available categories on Google Play for Android apps. App developers assign their application to a predefined list of app categories to help users to search for the most relevant apps in the Play Store. Throughout this thesis, map applications are defined as application from the Google Play Store which belong to the categories Maps and Navigation and Travel and Local (Play Console Help, 2025) as these two categories are explicitly related to mapping applications (Zingaro et al., 2023). The definition of the *Maps and Navigation* category is "Navigation tools, GPS, mapping, transit tools, public transportation" and that of *Travel and Local* category is "Trip booking tools, ride-sharing, taxis, city guides, local business information, trip management tools, tour booking" (Play Console Help, 2025).

3.1 Data Collection

This research builds upon data collected during the MapOnTap study, conducted by PhD candidate Donatella Zingaro at the Department of Geography, University of Zurich (UZH) (MapOnTap, 2020). The study is part of the Digital Society Initiative and focuses on understanding how individuals interact with mobile map applications in their daily lives. The primary goal of the MoT project is to enhance existing knowledge of mobile app usage, which serves as a fundamental step toward conducting more detailed investigations into smartphone use patterns. To support this research, the MapOnTap app was developed by the Geographic Information Visualization & Analysis (GIVA) group at UZH. It is based on the TapCounter app from QuantActions, a UZH spin-off company, which intentionally excludes location data. However, relying solely on tappigraphy data is insufficient for analysing the spatial context of smartphone usage, which is essential for understanding mobile map app interactions. To address this limitation, the MoT app captures touchscreen activity on Android devices using the tappigraphy method while also collecting GPS coordinate data and ambient light data to provide additional contextual information (MapOnTap, 2020).

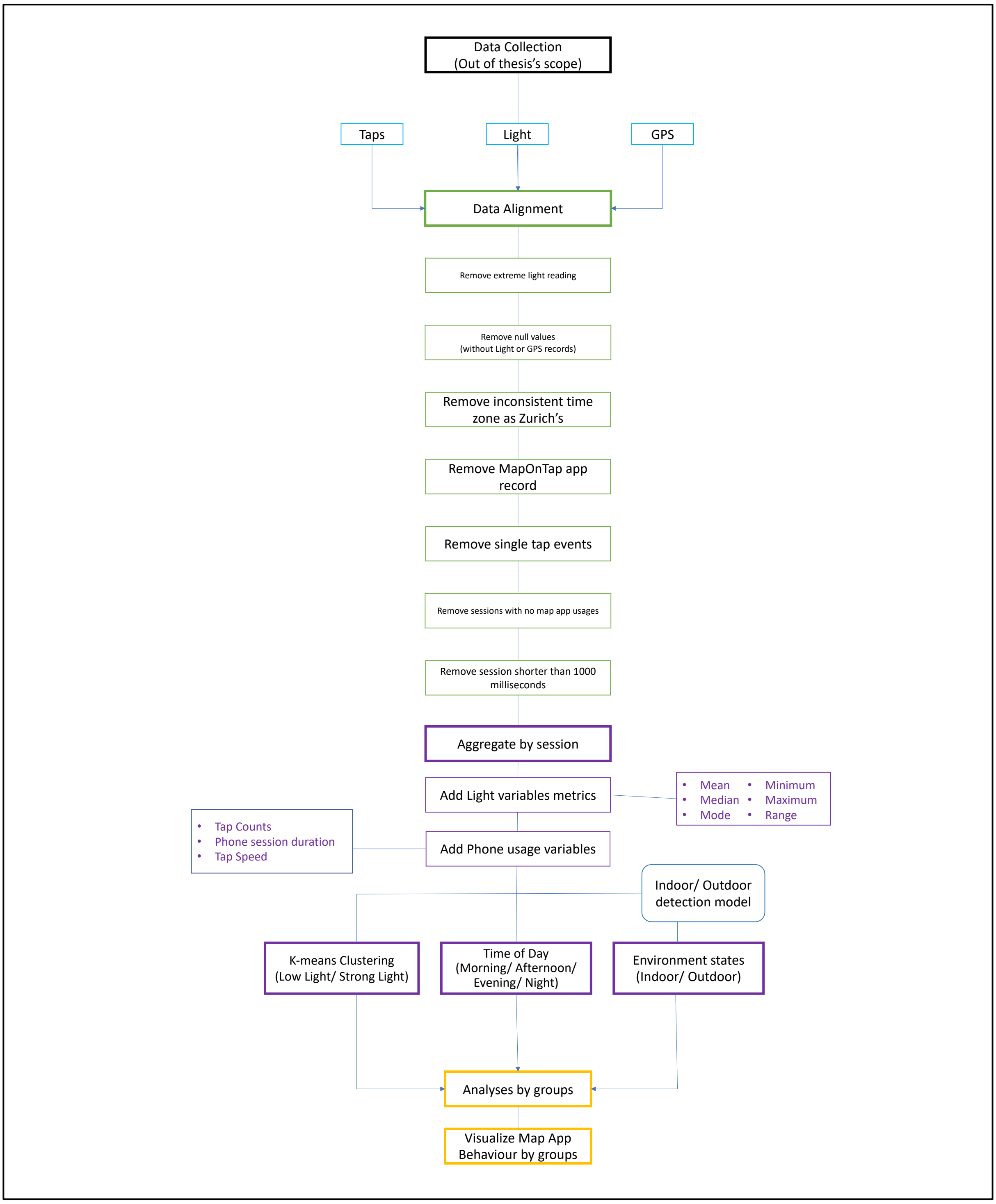


Figure 6. Workflow of Data Analysis

60 participants, with age between 18 and 85, joined the data collection period between March 2023 and June 2023. Participants were instructed to install the free *MapOnTap* app on their Android smartphones for a minimum two weeks and use the mobile phones as usual. The app functioned as

a tap-counting application that ran discreetly in the background. In addition to the tap data, participants were also asked to consent to the collection of their GPS data and the light sensor data for the purpose of this study. There were given the option to enable or disable the GPS tracking and light sensor at any time. At the end of the data collection period, they were compensated with a voucher of CHF 20 in Google Play Store. In order to protect the privacy of participants, all data is encrypted and no personally identifiable content as in text, images, browsing history or contact information was recorded.

Three types of data were obtained for this thesis, namely:

- Tap data
- GPS data
- Light sensor data

Tap data refers to the record each of the touchscreen interaction, including the unique identifier number of the session and that of the participant, timestamp of each tap on the phone (in milliseconds) made by the participants, the start time and end time of the session, the time zone of the participant's location, the name and the corresponding category of the app. Session in our data means the period from the phone was unlocked until it was locked again. The original data is recorded in individual tap level, this, the data would be aggregated into session level during the data pre-processing.

GPS data records the participants' coordinates, including the latitude, longitude, and altitude. Timestamps of GPS data are automatically recorded every 5 seconds. It is only recorded when movement is detected. In other words, the coordinates are not be updated if participants remains spatially stationary.

Light data is the reading of ambient light intensity measured in lux (lx). It is recorded from the build-in light sensor by Android Developers. The light sensor is usually on the top of the screen, nearby the front camera of mobile. It is also recorded in a fixed time interval like the GPS data.

3.2 Data Alignment

Since the tap data, GPS data, and light data are stored on individual servers, and participants might have different consent authorisations on MoT app and sensor tracking, the timestamps of the three datasets do not naturally align. To ensure consistency for further analysis, a 900-second alignment window was applied, linking tap records with any corresponding GPS and light data within this time frame. This approach ensures that sensor data captured at slightly different times can still be analysed together in a meaningful way. After alignment, key information from all three datasets, including tap timestamp, app details, participant identifiers, GPS coordinates, and light intensity readings, was merged into a single general data frame for further analysis.

3.3 Data Pre-processing

Prior to aggregation and analysis, data cleaning and pre-processing were performed. According to the standards of the National Optical Astronomy Observatory, the maximum sunlight can reach up to 107,527 lux (NOAO 2012) while the minimum light is 0.001 lux (Kyba et al., 2017). Even in the pitch-dark environments, the ambient light levels rarely reach absolute zero. In the collected dataset, the maximum light intensity record was 272,427 lux. The discrepancy is likely due to variations in sensor quality across different smartphone models and brands. Therefore, records with extreme ambient light values, either higher than 107,527 lux or exact zero values, were removed from the dataset. Some records had inconsistencies due to differences in user consent or app permissions, which caused missing timestamps (NA values). These were also filtered out to keep the analysis consistent.

Next, it is found that the timestamp had not been adjusted to the local time zone automatically. All timestamps are recorded in Zurich time. As such, if a participant travelled to foreign countries with different Coordinated Universal Time (UTC), the data showed incorrect times. Time is a crucial factor for ambient light, thus, data with time zones unmatched with Zurich was removed. This included London, Athens, Toronto, Kathmandu, Karachi and several regions across the United States; while those share the same time zone as Zurich are kept, including Paris, Berlin, Rome, Amsterdam and Warsaw. Duplicated timestamps are also removed. In addition, any tap data related to the MoT app (ch.uzh.geo.mapontap) was excluded, as MoT was a prerequisite for data collection and major part of the study set up itself, making it an unreliable indicator of actual map app usage.

Then, phone sessions that had only a single tap, and those with duration shorter than 1000 milliseconds (1 second) were removed. This issue is partly due to a known limitation of MoT. As mentioned previously, tap timestamps were recorded in milliseconds unit. The start time (phone unlock time) and end time (phone lock time) were however rounded to the nearest second. As a result, there may be cases where the start time is later than the first tap, or the end time is earlier than the last tap. Especially in sessions with only one tap, or where the only map tap happens right at the start or end, it is impossible to calculate the accurate map app usage duration. Thus, those sessions were dropped. Additionally, phone sessions with less than 1 second were also removed because tap speed (number of taps per second), as one of the map app usage variable, would be skewed in such cases. For example, a single tap within half a second would result in a tap speed score being doubled. It is also worth mentioning that phone sessions with duration of less than 1 second could be accidental screen touches which are not considered a valid indicators of real, intentional app usage.

Finally, since the raw tap dataset was massive and only a small portion of it was related to map apps usage, only sessions with at least one map app tap were kept for further analysis. This helped to reduce noise and focus more clearly on map app behaviour examination.

3.4 Data Aggregation

After cleaning the data, the tap-level data was further aggregated into session-wise level. This aggregation process involved extracting the key information including: unique session identifier, start time and end time of each session, participant identifier, and time zone. For the independent variables, ambient light, session-wise light metrics were aggregated using mean, median, minimum, maximum, mode, and range based on the light intensities along with each taps within the session. As for the dependent variable, map app usage, three main variables are used and the following sub-variables were derived:

Map App Usage Variables:

- Tap Counts: Total tap counts/ map app tap counts/ map app tap count proportion
- Phone Session Duration: Total phone session duration / map app duration/ map app duration proportion
- Tap Speed: General tap speed/ map app tap speed

Light variables:

- Light conditions: Low Light / Strong Light
- Time of day: Morning / Afternoon / Evening / Night
- Environmental states: Indoors / Outdoors

The influence of light are examined base on light conditions, temporal differences and spatial differences.

1. Light Conditions: First, the light conditions are classified using K-means clustering method, an unsupervised machine learning algorithm that groups unlabelled data points into distinct clusters (IBM, 2024). K-means is widely applied due to its simplicity, high efficiency, and ease of implementation (Chong, 2021). The optimal number of clusters will be determined using the elbow method, a graphical technique for identifying the appropriate number of clusters in K-means.
2. Temporal differences: The session-wise data will be divided into four groups base on the dominant time of the day: Morning (6AM – 11AM), Afternoon (12PM – 5PM), Evening (6PM – 11PM), Night (0-5AM).
3. Spatial differences: Each session is labelled as either indoor or outdoor based on the mode of the environmental states. The method for classifying indoor and outdoor environments will be explained in the following subsection 3.6 Indoor Outdoor environment classification.

3.5 Data Visualization and Analysis

A correlation test and regression test are first conducted to examine if there is any significant relationship between the light variables and map app usage variables. After visualising the variables in different groups, statistical tests are conducted to assess whether significant differences exist between the groups, both at the group level and individual map app levels The Mann-Whitney U test is applied for comparisons involving two elements within groups while the Kruskal-Wallis test is applied for comparing more than two elements within groups.

3.6 Indoor/ Outdoor Environment Classification

To classify whether a tap was made indoors or outdoors, I set up three different models for testing. The first model relied solely on whether the point fell within the building footprints. The second one used only the ambient light intensity. And the third algorithm considered both factors to form a lightweight approach of indoors and outdoors detection.

The building footprint data was downloaded from OpenStreeMap. Due to the large size of the dataset, downloading all buildings information across Europe, even only consider those countries in the same time zone as Switzerland, such as Italy, France and Germany, was too heavy which might cause long loading time and frequent crashes. Therefore, only map taps made within Switzerland were included in the indoors and outdoors classification. To ensure the relevant points were within Switzerland, a DBSCAN (Density-Based Spatial Clustering of Applications with Noise) was used to check whether the majority and the centroid of the map points fell within Swiss borders. To retrieve building boundary information, first, bounding boxes were created for different cantons in Switzerland. These boxes were kept as small as possible to reduce memory usage while still fully covering all map points. The buildings boundary information was then saved in a folder named "switzerland_buildings" in GeoJSON format. Given that GPS accuracy and building footprint might not be very precise, a 1-m buffer was added around all building footprints. If a map point fell within the buffered footprint, it was classified as indoors; if it was outside, it was considered outdoors.

For the ambient light-only method, the threshold was set at 1200 lx for daytime and 100 lx for night time. Since the study period spanned from March to June, which the sunrise and sunset hours varies by seasons and the cities, the average sunrise and sunset time was considered (Time and Date AS, 1995-2025). The definition of daytime is from 7am - 6pm for March, 6am - 8pm for April and May, and 5am - 9pm for June. Anytime outside these range was considered as night time. If the light intensity of a map point exceeded or equalled to 1200 lx at daytime, or lower than 100 lx at night, it is regarded as outdoor; Otherwise, if it was lower than 1200 lx during the day or higher than 100 lx at night, it was classified as indoors.

For the joint detection, lightweight method, both ambient light and the location factors are considered. The workflow of the algorithm is illustrated in Figure 7. The priority of the model is to check the time of the session to see whether it occurred during the day. Then it checks the light intensity, using the same threshold as in the light-only method. Finally, it considers whether the tap happened inside a building footprint. From the workflow of Figure 7, there are six possible outcomes, with four outdoors and two indoors scenarios.

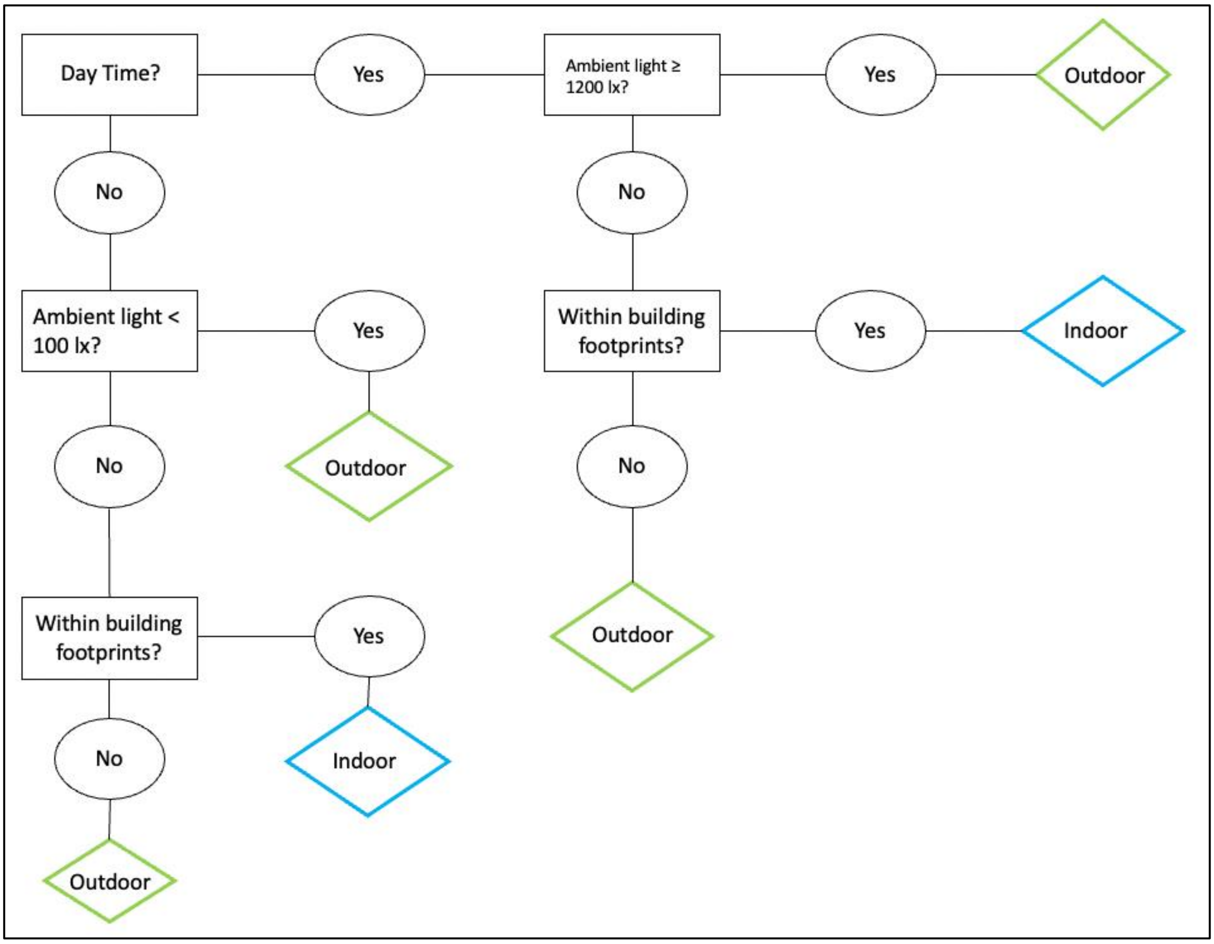


Figure 7. Flowchart of Indoor & Outdoor classification

There are no ground truth labels for the environmental states available to validate the accuracy of the models, as it was not the original research purpose of MoT during the data collection period. As a workaround, I manually selected 530 reference points to define indoor and outdoor states based on visual inspection via aerial photo and contextual understanding. To ensure reliability, only points that clearly meet criteria were included. Since it is challenging to classify semi-indoor and semi-outdoor spaces (Radu et al., 2014), this thesis only focuses merely on two basic environment, indoors and. Any ambiguous locations were excluded for the reference points. For example, for indoors location, only buildings with no rooftops are considered. For places like train stations, as it is tricky to define whether it is indoor and outdoor on the open platform areas, only those points inside the fully enclosed, inner building part (like the mall area in Zurich Hauptbahnhof) are considered for reference checking. Moreover, map points located on roads are not considered as reference points since it is difficult to determine whether the participants are commuting in transportation or not; and even if it is the case, it is still vague to define whether one on transportation mode is identified as indoors or outdoors. For outdoor classification, only those points in clearly open environments were considered, such as mountainsides, lakeshores, or open spaces in the parks. Table 5 below shows four reference points with a comparison among three models, including the time, date, ambient light, and location description, as well as the map from OSM and the aerial views from Google Maps.

After selecting the 530 reference points, with 247 indoors points and 283 outdoors points, there were used to evaluate the performance of the three classification models. Accuracy, precision, recall, and F1 score were calculated by comparing the model outputs with the reference points. The model with the best overall performance was then chosen to classify the remaining data. Since the map points are at tap level, the environmental state was further aggregated to the session level by taking the mode of the environmental states across all taps within each session.

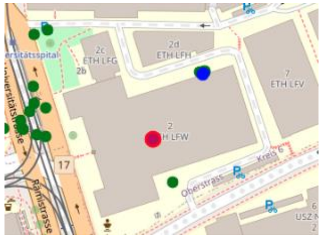
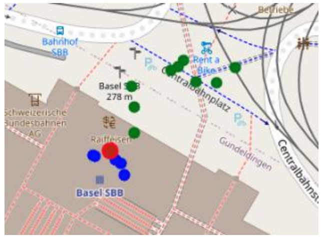
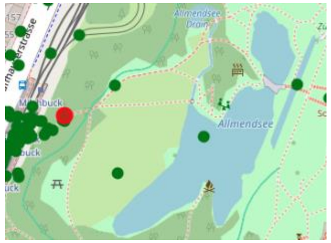
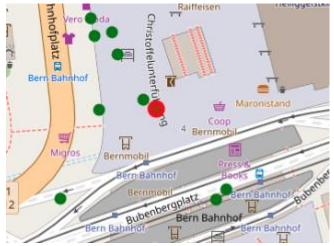
Point Index	385	12345	24764	36814
Location	ETH’ s LFW building	Basel Hauptbahnhof	Irchel Park	Bern Hauptbahnhof
Date & Time	2023-05-12 7:10:35 AM	2023-06-10 09:20:05 AM	2023-05-08 5:24:22 PM	2023-06-26 1:46:14 PM
Ambient Light	179 lx	20693 lx	3.2375 lx	6164 lx
Map point on OSM				
Aerial Photo on Google Maps				
State by building	Indoor	Indoor	Outdoor	Indoor
State by ambient light	Indoor	Outdoor	Indoor	Outdoor
State by joint method	Indoor	Outdoor	Outdoor	Outdoor
State by manual examination	Indoor	Indoor	Outdoor	Outdoor

Table 5. Sample of reference points comparison among 3 models and manual examination

4 Result

This chapter presents the finding of the data analysis, including the descriptive statistics, visualisation, the statistics test results, and the analysis of the indoor and outdoor detection model.

4.1 Indoor Outdoor Model Detection

Among out total data frame of 335,664 taps, 72,295 taps are related to map app usage. Due to computer memory size limitation for downloading building footprints from OSM, it is decided to only download those map points happened in Switzerland. It is supported by the DB Scan result as shown on Figure 8 where the centroid cluster is within or nearby Switzerland.

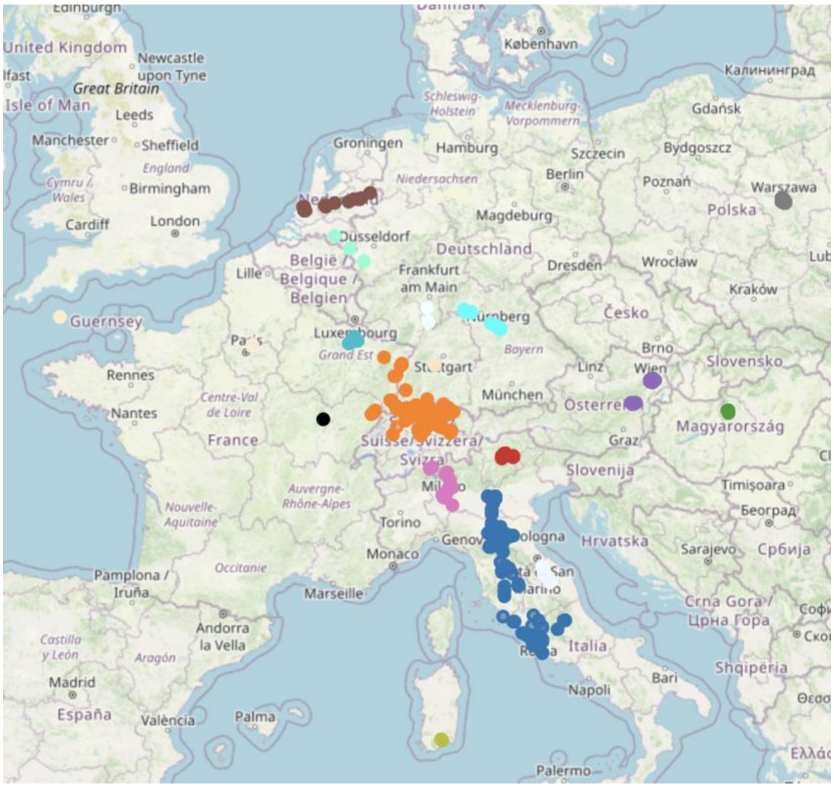


Figure 8. DB Scan result for all map points

After filtering out the map points within the boundary of Switzerland, there are 42,106 map points. The three models, the first one identify the indoor and outdoor environment by solely 1m buffer of building footprints downloaded from OSM, the second one solely considers the ambient light intensity, and the third model which is a self-defined algorithm considered both the building footprints and ambient light factors, were carried.

Base on the building footprints-only model, there are 25,085 outdoor map taps (59.6%) and 17,021 indoor map taps (40.4%). Base on the detection method by mere light intensity, there are 11,164 outdoors taps (26.5%) and 30,942 indoors taps (73.5%). Based on the lightweight, self-defined function, there are 27,692 outdoors taps (65.8%) and 14,414 (34.2%) indoors taps.

By comparing the 530 reference points and the results of the three models, the accuracy, precision, recall, and F1-score, are shown in Table 6.

Models:	Accuracy	Precision	Recall	F1 Score
Only Building Boundary	0.7925	0.7438	0.8462	0.7917
Only Light Intensity	0.7321	0.6981	0.7490	0.7227
Joint Method	0.8113	0.9106	0.6599	0.7653

Table 6. Accuracy, precision, recall and F1 score of the 3 indoor outdoor detection models

The accuracy and precision score of the self-defined, lightweight method is highest, and performance of the light-only model is the worst with lowest accuracy, precision and F1 score. Thus, the 42,106 map points in Switzerland are classified to be indoors and outdoors usage via the lightweight algorithm considered both the building footprint and ambient light. It is then further aggregated into 1,820 phone sessions by the mode of the environmental states. There are 384 indoor session and 1,211 outdoors sessions, involving 30 participants.

4.2 General Descriptive Statistic

In the initial aligned dataset with combined taps, light and GPS data, there are 60 participants, encompassing 5,428,998 taps, across 47,757 phone sessions. The data cleaning process involved several filtering steps. I first removed 609 records (0.01%) with light intensity exceeding 107,527 lux as extreme values, and eliminated 983,321 records (18.11%) with null light values. Additionally, I excluded 397,620 records (7.32%) with time zones inconsistent with Zurich and removed 734,490 duplicate timestamp records (13.53%). 27,593 tap events (0.51%) related to the MapOnTap app were also deleted. These initial cleaning steps reduced the dataset to 3,285,365 tap records from 51 participants across 34,490 phone sessions. Further refinement was conducted by retaining only sessions with at least one map app tap and removing 134 single tap events due to time unit limitations for session duration calculation. Moreover, 49 sessions with phone session less than 1000 milliseconds (i.e. 1 second) and 167 sessions with map app usage duration less than 1000 milliseconds were removed. Consequently, the final dataset comprised 335,664 tap records from 48 participants involving 2,938 phone sessions.

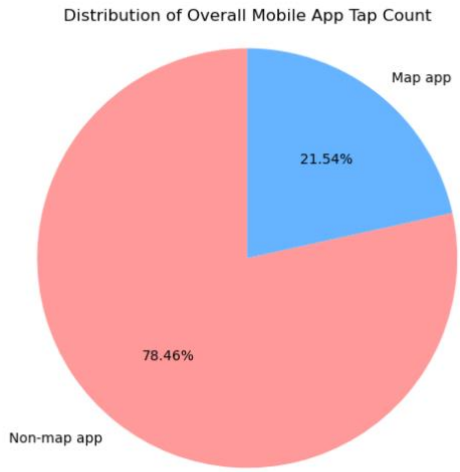


Figure 9. Distribution of Tap Counts for Map App and Non-Map App Usage

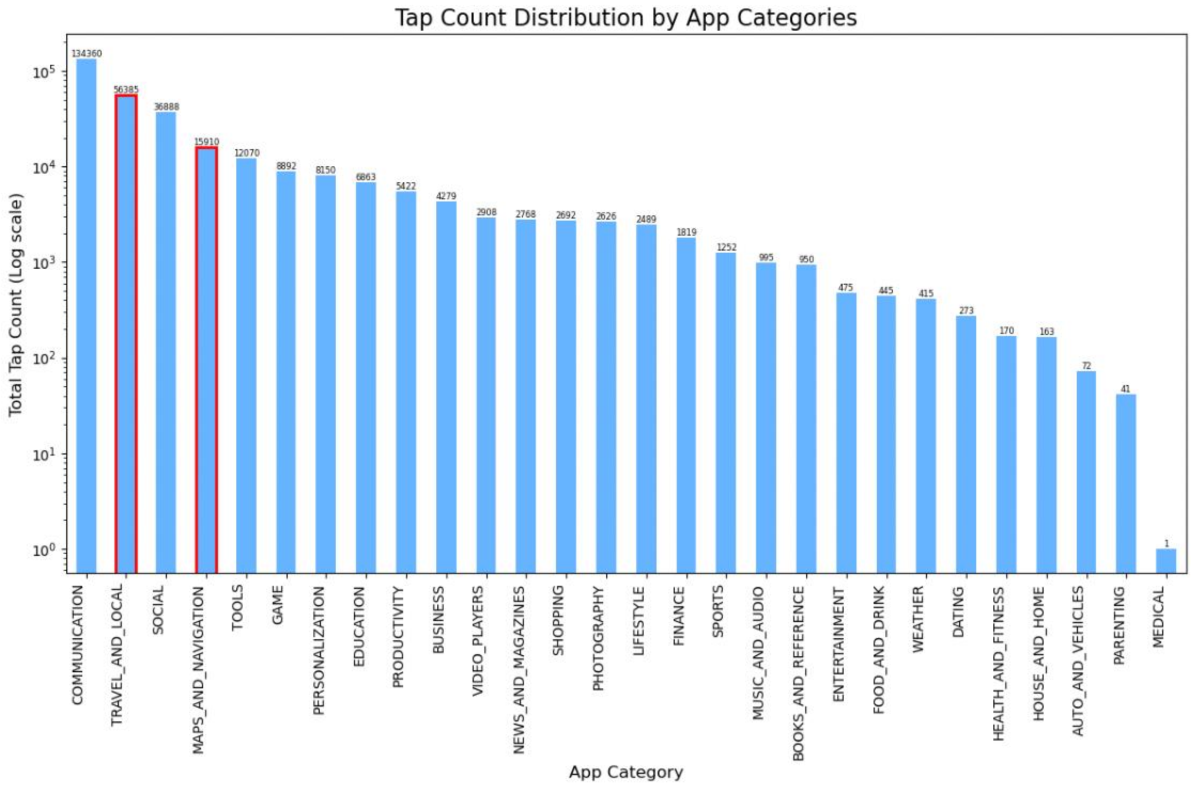


Figure 10. Distribution of Tap Counts of all categories

Among the 335,664 taps, 263,369 taps (78.46%) are non-map app usage, and 72,295 taps (21.54%) are map app usage (Figure 9). Figure 10 shows the log-scaled distribution of all app categories. Among the 28 app categories involved, the top three categories used are *Communication* (40.03%), *Travel and Local* (16.80%), and *Social* (11.00%)). The three least used categories are *Medical* (0.0003%), *Parenting* (0.012%) and *Auto and Vehicles* (0.022%). Map app in this thesis refers to only *Travel and Local* and *Maps and Navigation* categories. The Sankey diagram in Figure 11 shows the distribution of these two categories and the map app involved. Overall, the usage of *Travel and Local* (56,385 taps, 16.80%) is higher than *Maps and Navigation* (15,910 taps, 4.73%).

Among the *Travel and Local* category, *Google Maps* is the most used apps (49,715 taps, 88.17%), followed by *Airbnb* (824 taps, 1.46%), *Booking.com* (666 taps, 1.18%), *Switzerland Mobility* (659 taps, 1.16%) and *Flixbus* (618 taps, 1.10%). Other apps in *Travel and Local* category such as *OpenStreetMap* (OSM+), *DB train, SNCF train, Trenitalia, Skyscanner, Baidu Map, IskiSwiss, Limebike* etc.

Among the *Maps and Navigation* category, *SBB mobile* is the most used apps (8356 taps, 52.52%), followed by *Mapy* (2761 taps, 17.35%), *Swisstopo* (1451 taps, 9.12%), *Iternio* (420 taps, 2.63%) and *Altoadigetogo* (356 taps, 2.23%). Other apps in *Maps and Navigation* such as *ZVV, Fairtiq, Uber, Mobility.ch* etc.

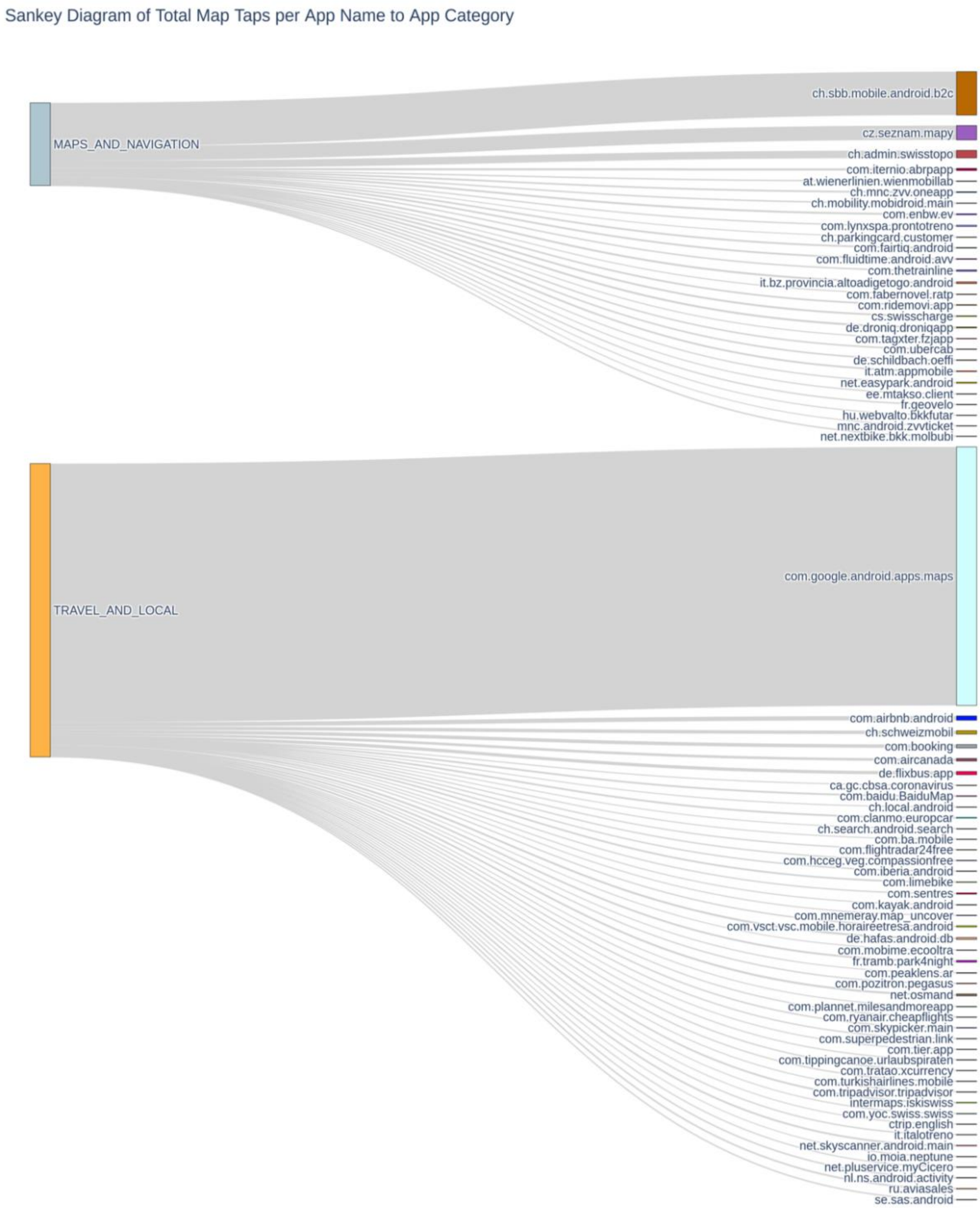


Figure 11. Sankey Diagram of Map App Distribution

Table 7 displays the top 20 used map app along with their tap counts, tap count percentage of all map app usage, the number of participants who used those app, and the percentage of all participants who engaged in the study. The most popular map app is *Google Maps* with 44 out of 48 participants (91.67%) using it during the study period. It is followed by *SBB Mobile*, which was used by 28 out of 48 participants (58.33%). 7 participants used *Booking.com*; 6 participants (12.5%) involved with

Flixbus and *DB train*; 5 users (10.42%) have used *Airbnb* app; and 4 (8.33%) have interacted with *Swisstopo* and *Switzerland Mobility*.

Rank	App Name	Total Count	Percentage of total map app count	Number of Participant involved	Percentage of involved participants (out of 48 participants)
1	com.google.android.apps.maps	49715	68.77	44	91.67
2	ch.sbb.mobile.android.b2c	8356	11.56	28	58.33
3	cz.seznam.mapy	2761	3.82	2	4.17
4	ch.admin.swisstopo	1451	2.01	4	8.33
5	com.airbnb.android	824	1.14	5	10.42
6	com.booking	666	0.92	7	14.58
7	ch.schweizmobil (*Switzerland Mobility*)	659	0.91	4	8.33
8	de.flixbus.app	618	0.85	6	12.50
9	com.aircanada	495	0.68	1	2.08
10	com.iternio.abrpapp	420	0.58	1	2.08
11	net.osmand	387	0.54	1	2.08
12	de.hafas.android.db (*DB Train*)	380	0.53	6	12.50
13	fr.tramb.park4night	359	0.50	1	2.08
14	it.bz.provincia.altoadigetogo.android	356	0.49	1	2.08
15	com.thetrainline	287	0.40	1	2.08
16	com.lynxspa.prontotreno	260	0.36	2	4.17
17	com.vsct.vsc.mobile.horaireetresa.android (*SNCF*)	260	0.36	2	4.17
18	com.sentres	243	0.34	1	2.08
19	net.easypark.android	232	0.32	2	4.17
20	de.droniq.droniqapp	185	0.26	1	2.08

Table 7. Top 20 used map app with tap counts and participants numbers

4.2.1 Light Variables Descriptive Statistics

Each tap records is associated with an individual light intensity reading. Among the 335,664 light records, the average light intensity is 1,386.00 lux, ranging from a minimum of 0.000011 lux to a maximum of 105,489 lux. The first quartile is 21 lux, the median is 105.67 lux, and the third quartile is 435.37 lux. The standard deviation is 6,461.58 lux, indicating high variability. The distribution is strongly right-skewed, with most readings concentrated at lower illuminance values.

During the aggregation process, light data was summarized using six statistical measures: mean, median, mode, minimum, maximum, and range. Table 8 presents the descriptive statistics and skewness of the light metrics for 2938 phone sessions and Figure 12 visualised the light intensity distribution in a log-transformed bar chart. From the skewness value and the distribution, it is observed that the metrics are right-skewed towards the low reading.

Unit: Lux	Light (mean)	Light (median)	Light (mode)	Light (minimum)	Light (maximum)	Light (range)
Mean	3001.16	2991.82	2985.56	1994.52	4211.13	2216.62
SD	8738.97	9483.28	9550.27	6949.06	11637.24	9115.92
Min	0.14	0.00	0.00	0.00	0.14	0.00
First quartile	38.52	30.64	27.50	13.80	53.32	0.00
Median	225.94	189.33	177.85	111.64	292.53	11.00
Third quartile	1305.49	1198.50	1150.16	636.43	2037.51	335.81
Max	96670.14	103508.24	103508.24	84906.38	105489.00	105400.00
Skewness	5.26	5.64	5.67	6.36	4.67	6.56

Table 8. Descriptive statistics of ambient light by session

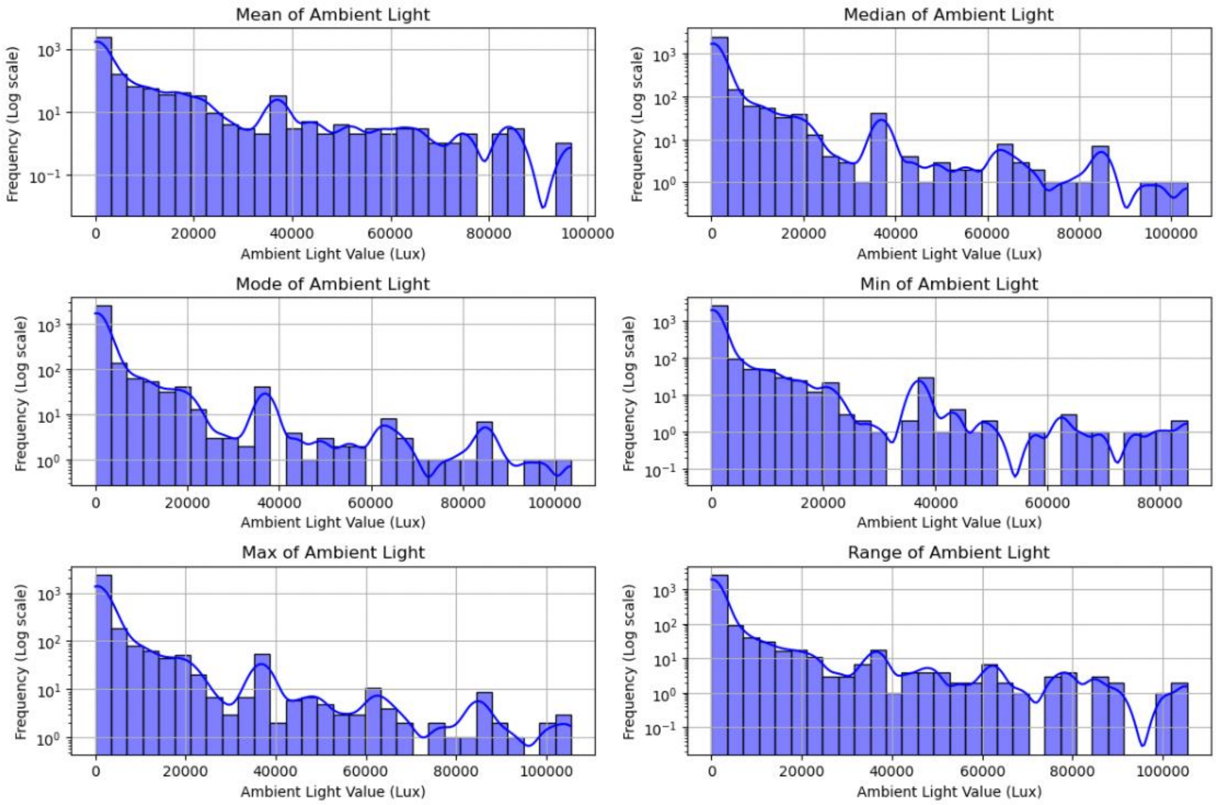


Figure 12. Log-Transformed distribution of light variables

4.2.2 Map App Usage Variables Descriptive Statistics

Among the 2,938 phone sessions with map app usage, the session with most tap counts contains 5,482 taps, with 14 map app tap (0.25% of total taps in session). The session with highest map app tap contains 2,090 total tap counts, with 2,009 map app taps (96% of total taps in session). The longest phone session lasts for 14,710,024 ms (4 hours and 5 minutes), with 24,181 ms (24.3 seconds) spent in map app, accounting for 0.16% of the total phone session duration. The longest map app usage duration is 5,739,307 ms (1 hour and 36 minutes) out of 6,129,466 ms (1 hour and 42 minutes) which constitutes 93.63% of the total phone session duration.

The map app tap count proportion ranges from 0.05% to 100%. There are 572 sessions with 100% map app tap count (indicating full map app usage throughout the phone session) with map app tap counts ranging from 2 to 380 taps.

To view the hourly and weekly pattern in the usage of map app, heatmaps of normalised map app tap count proportion (Figure 13) and normalised map app duration proportion (Figure 14) are presented below. In Figure 13, it is observed that the map app usage is generally higher on Friday, Saturday and Sunday. Usage tends to be higher during daytime hours (from 7am to 8pm). A minor trend is observed between 3 and 5PM on Tuesday and Thursday. The peak hour of usage is Friday at 5PM (52.67), followed by Sunday at 1PM (48.45) and Saturday at 1PM (41.18).

Figure 14 presents the heatmap of map app duration proportion over the week. Similar to the map app count proportion, map app usage is higher from Friday to Sunday and more active during the daytime (from 7 am to 8 pm). The peak hour for map app duration is Friday at 5PM (55.22), followed by Sunday at 1PM (50.14) and Saturday at 1PM (40.84).

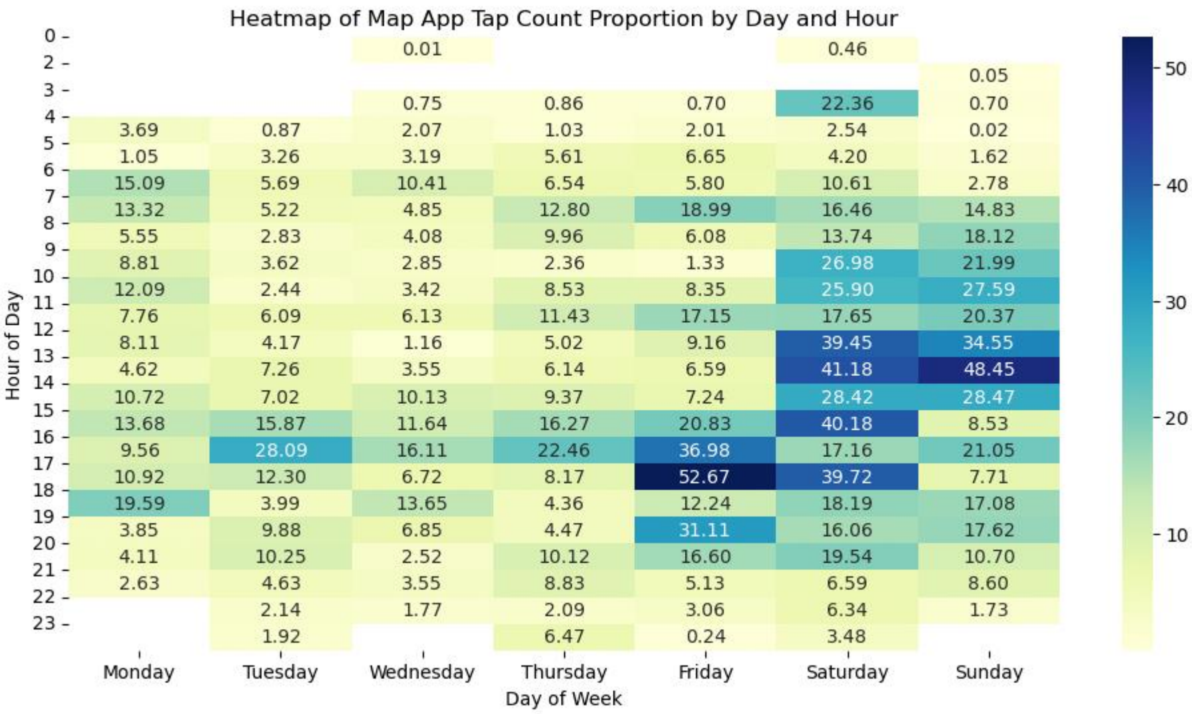


Figure 13. Heatmap of Map App Tap Count Proportion by Day and Hour

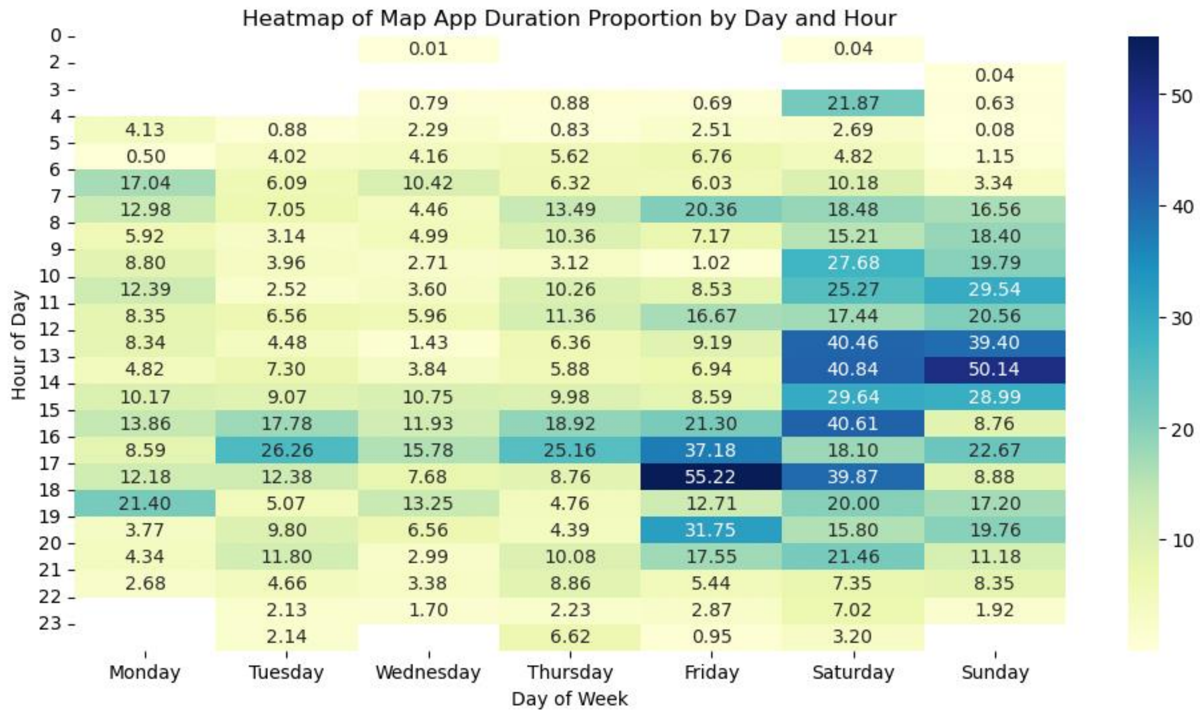


Figure 14. Heatmap of Map App Duration Proportion by Day and Hour

Since it is already known Google Maps is the most used map app, from the Sankey Diagram in Figure 11 and the popularity showed in Table 7, Figure 15 and Figure 16 display the normalised Google Maps tap count and duration respectively. Friday and Saturday are the most active days, followed by Sunday and Tuesday. The periods from 6 - 7AM and 4 – 8 PM show higher activity on weekdays while Friday and weekend has higher usage in general. The peak tap count usage for Google Maps occurs on Friday at 5PM (22.76), followed by Saturday at 5PM (22.38), 3PM (19.04) and 1PM (15.77). The heatmap of Google Maps Duration on Figure 16 shows similar pattern, with higher activity observed from 6-7 AM in the morning and 4 PM to 7 PM in the afternoon on weekdays, while Friday and the weekend generally see higher usage. The peak duration peak for Google Maps usage is again on Friday at 5PM (40.68), followed by Saturday at 5PM (40.31), 3PM (33.54) and 1PM (30.61).

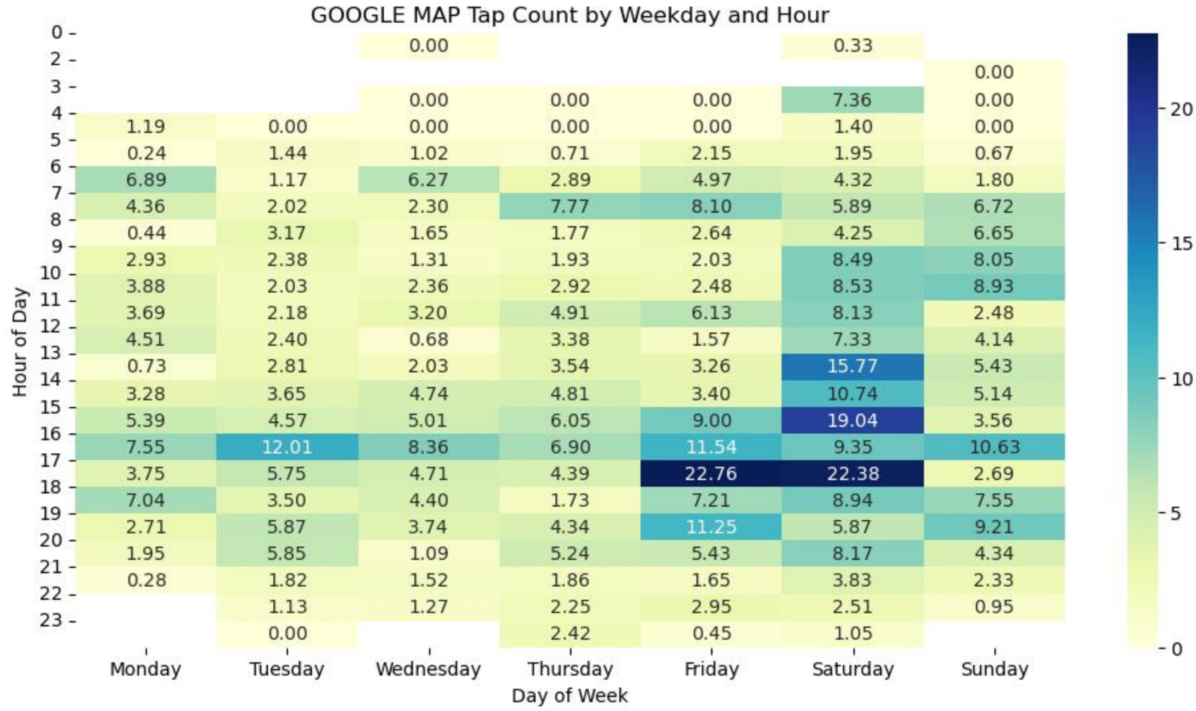


Figure 15. Heatmap of Google Maps Tap Count by Day and Hour

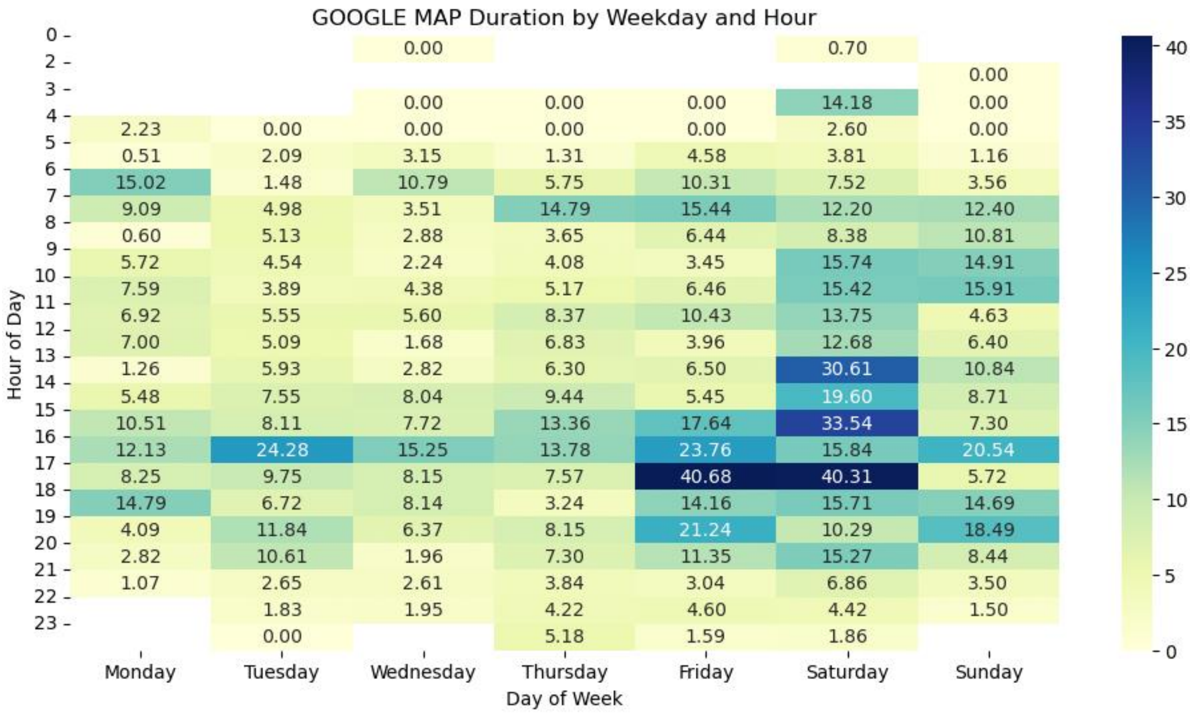


Figure 16. Heatmap of Google Maps Usage Duration by Day and Hour

4.3 General Correlation & Regression

Figure 17 presents the Spearman correlation metric heatmap for light intensity variables and map app usage variables. The Spearman corelation method was chosen as the variables do not follow a normal distribution, confirmed by skewness checks and Shapiro-Wilk test.

From the correlation matrix, no significant correlation was found between the mean, median, mode, minimum, and maximum light intensity per session and map app usage variables, as all R-values were below 0.2 with significance value (p-value) over 0.05. However, the light range metric exhibited mild to moderate correlations with map app usage variables.

Specifically, light range shows a mild positive correlation with total tap count per session ($r = 0.4668$, $p < 0.01$) and map app tap count ($r = 0.2511$, $p < 0.01$). Interestingly, a slight negative correlation was found between light range and map app tap proportion ($r = -0.3121$, $p < 0.01$).
For the duration-related variable, light range shows a moderate positive relationship with total session length ($r = 0.5606$, $p < 0.01$) and a slight positive correlation with map use length ($r = 0.4024$, $p < 0.01$). It also exhibited a low negative correlation with map app length duration proportion ($r = -0.2909$, $p < 0.01$).
Regarding tap speed, light range shows a slight negative correlation with general tap speed ($r = -0.2485$, $p < 0.01$) and with map app tap speed ($r = -0.2742$, $p < 0.01$).

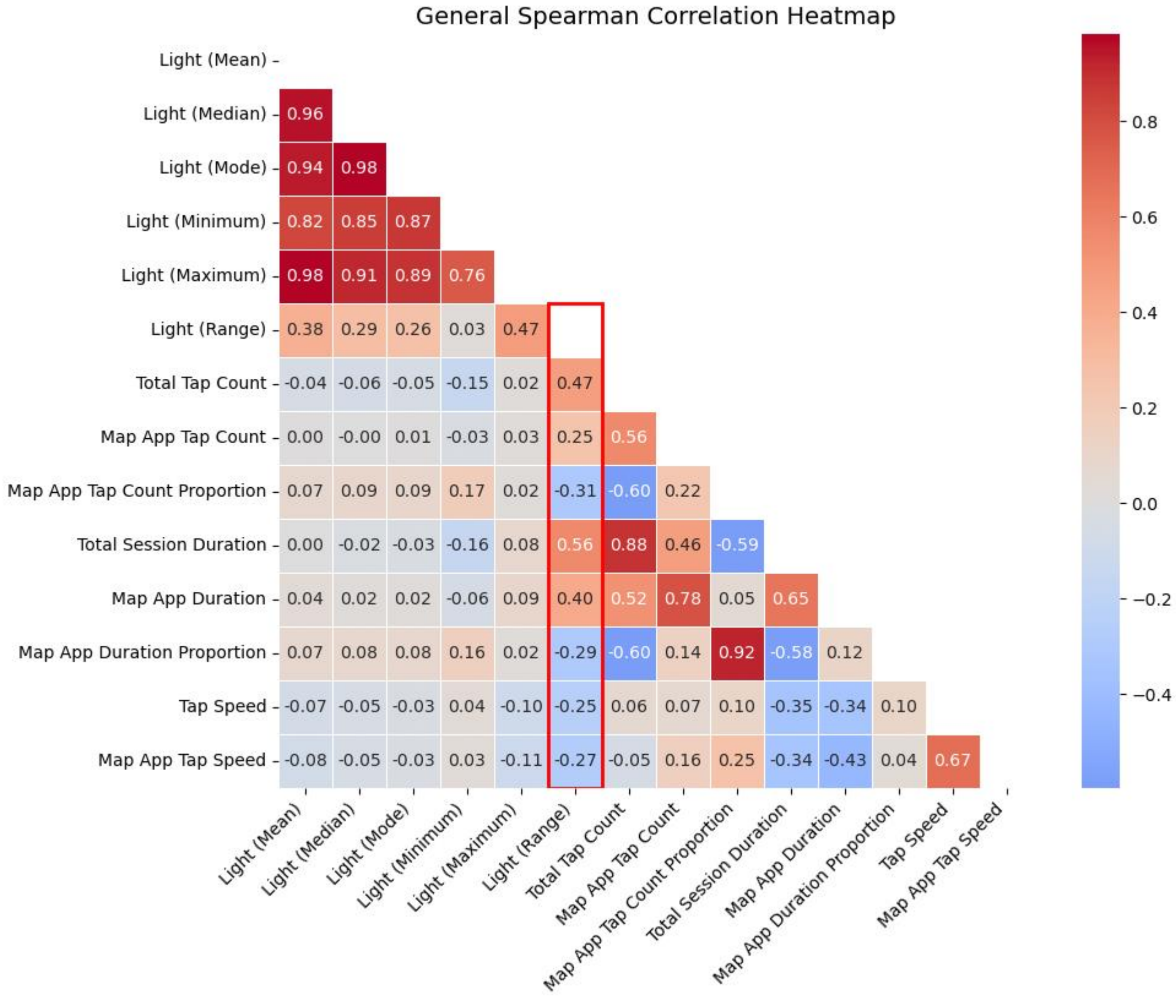


Figure 17. Spearman correlation heatmap among the light variables and map app usage variables

The regression plots in Figure 18 further illustrate these relationships with correlation coefficients and significance values. They indicate that light range is positively associated with total tap count, map app tap count, overall session duration, and map app usage duration, implying that greater variations in ambient light within a session correspond to prolonged phone usage. However, slight negative regression trends are observed between light range and map app tap proportion, map app duration proportion, overall tap speed, and map app tap speed. This suggests that users may engage less with map apps when ambient light fluctuates intensively within the same phone session.

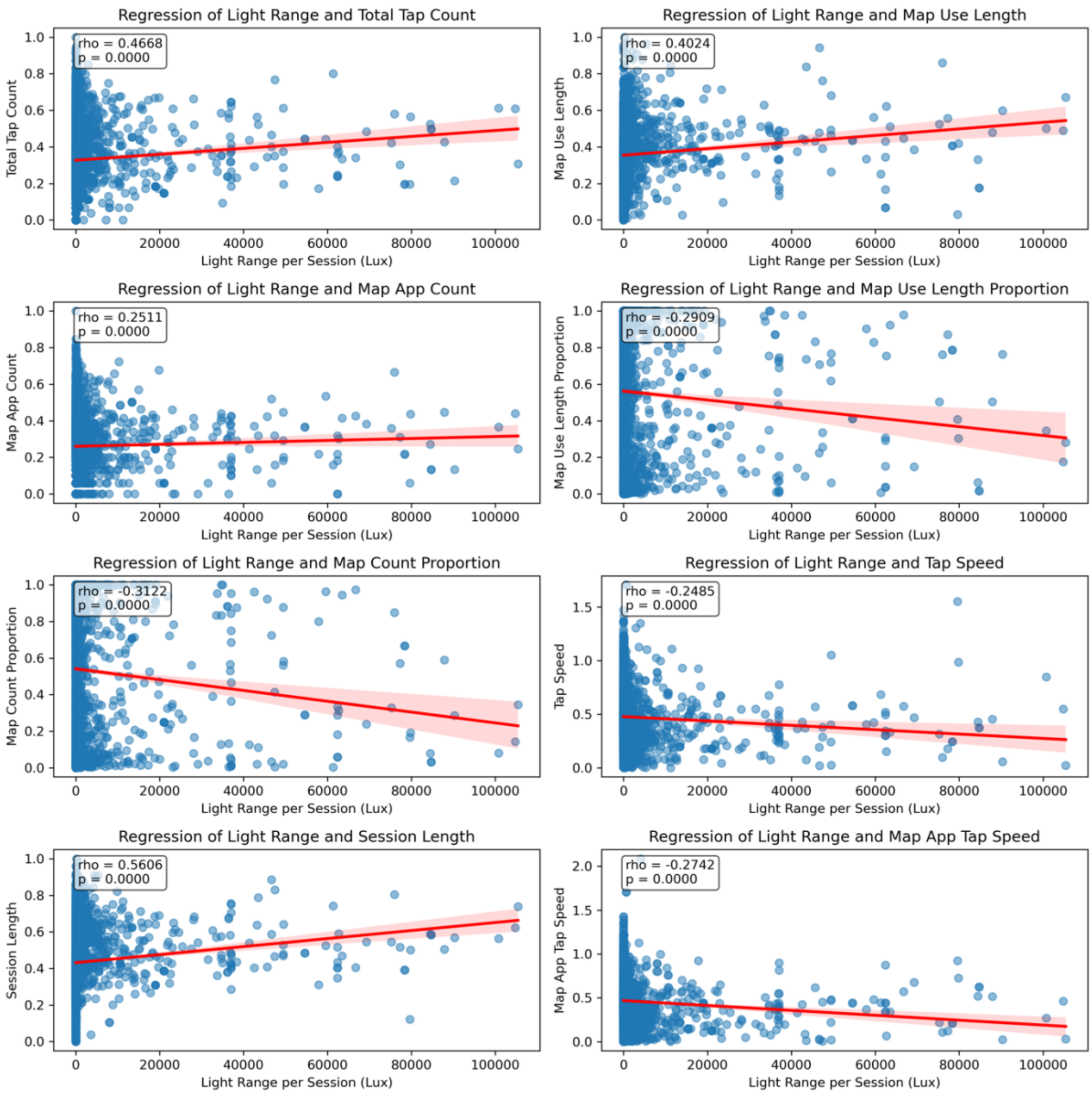


Figure 18. Regression plots for light range and map app usage variables

4.4 Light Variation by K-means clustering

Given that all distributions are highly-right skewed (as shown on Figure 12), the mean light intensity over the session was selected as the primary metric for clustering, as it provides a more stable representation of overall light exposures across sessions, compared to more extreme values like the range or median. The elbow method (Figure 19) shows that 2 clusters would be the most optical number of clusters, confirmed by silhouette score 0.92 for 2 clusters; and 0.87 for 3 clusters and 4 clusters.

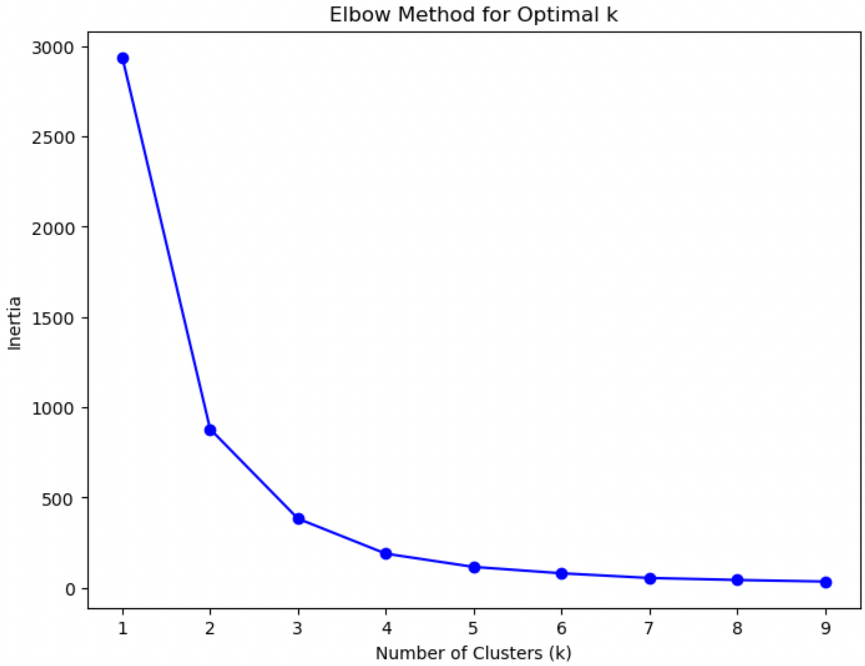


Figure 19. Elbow Method Plot for Determining Optimal Number of Clusters

Figure 20 presents the boxplot of ambient light readings for the two clusters identified using K-means clustering. The Low Light cluster contains 2,853 counts while Strong Light cluster consists 85 counts.

For the Low Light cluster, the light intensity ranges from 0.13625 to 23,492 lux. The interquartile range (IQR) spans from 36.17 lux to 1,161.62 lux. The mean for this cluster is 1,738.72 lux, with a median of 204.64 lux and a standard deviation of 3,903.91 lux. The distribution of Low Light is highly skewed with many outliers present above the upper whisker.

For the Strong Light cluster, the ambient light readings range from 23,789.34 lux to 96,670.14 lux. The IQR extends from 37,066 lux to 53,117.17 lux, with a mean of 45,374.44 lux, a median of 37,066 lux, and a standard deviation of 16,785.67 lux. The distribution of Strong Light cluster is less skewed compared to the Low Light Cluster though a few outliers exist.

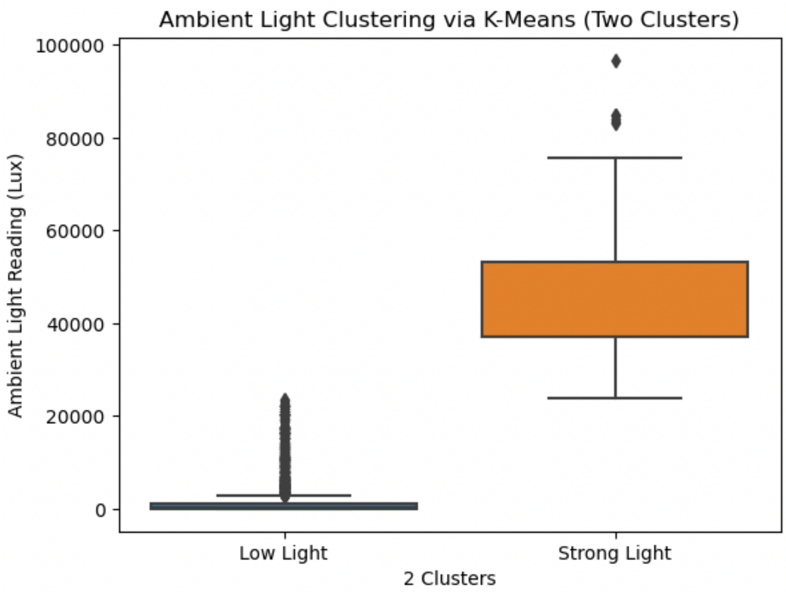


Figure 20. Boxplots of 2 K-means Clusters

4.4.1 General Map App Usage across 2 lighting condition clusters

The map app usage variables were analysed after clustering. Figure 21 presents boxplots comparing the total tap count, map app count, and map app tap count proportion across the two lighting condition clusters. To statistically assess differences between clusters, a Mann-Whitney U test was conducted for each variable.

The median total tap count was slightly higher in the Low Light cluster (Median = 0.31, Min = 0, Max = 1, SD = 0.20) compared to the Strong Light cluster (Median = 0.28, Min = 0, Max = 0.64, SD = 0.15), indicating more frequent phone interactions in low light condition. The median of map app tap count is 0.25 for Low Light cluster (min: 0, Max: 1, SD: 0.16) and 0.23 for Strong Light cluster (Min: 0, Max: 0.57, SD: 0.14). There is no clear visual difference on the boxplot. For the map app tap count proportion, the median is 0.55 for Low Light cluster (Min:0, Max: 1, SD: 0.37) and 0.75 for Strong Light cluster (Min: 0.0075, Max: 1, SD: 0.36). The map app tap count proportion is higher in Strong Light cluster by the boxplot.

These observations were supported by the Mann-Whitney U test. There is a significant difference in total tap count ($U = 143{,}832.5$, $p < 0.01$) and map count proportion ($U = 101{,}071.0$, $p < 0.01$) among the two clusters. In contrast, the map app count does not have significant differences among clusters

(U = 128,379.5, p > 0.05). These findings indicate that the overall tap count number is higher in low light condition but higher map app usage in terms of tap count proportion in bright light condition.

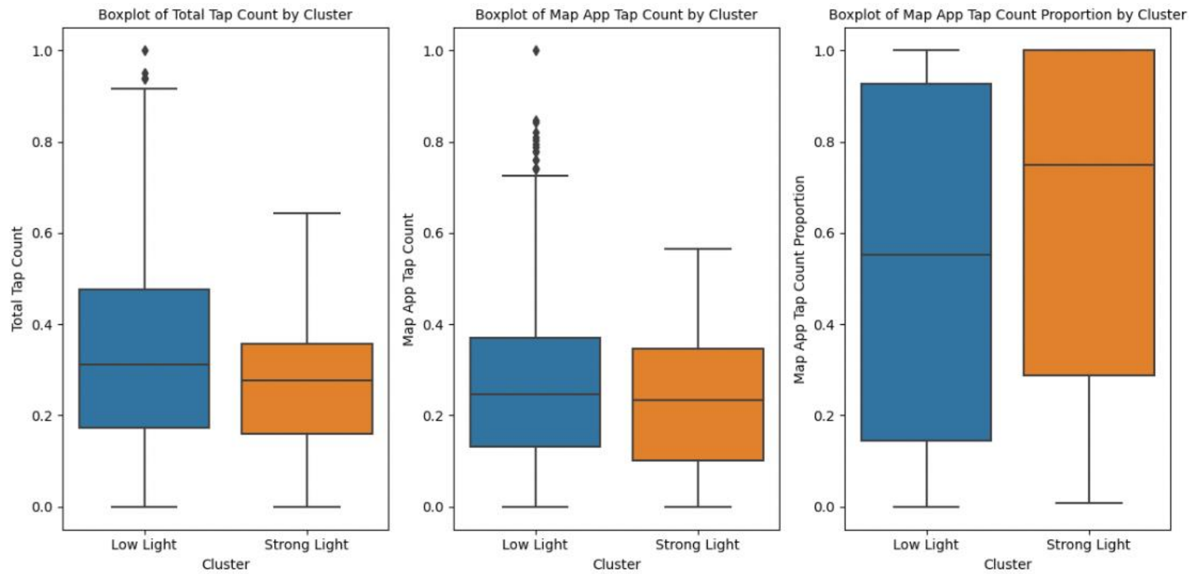


Figure 21. Boxplots of total tap count, map app count and map count proportion by 2 Lighting Condition Clusters

Figure 22 presents boxplots comparing the total session length, map app usage length, and map app usage length proportion across the two clusters. From the boxplots, we observe that Low Light (median: 0.43) cluster has longer phone sessions than Strong Light (0.38) in general. The difference in map app usage length is not very clear (median at 0.3639 and 0.3674 for Low and Strong Light cluster respectively), while the map app length proportion appears to have a higher usage in Strong Light cluster (median: 0.73) than Low Light cluster (Median: 0.58). The Mann-Whitney U test results indicate a significant difference in total session duration (U = 140,742.5, p < 0.05) and map app duration proportion (U = 104,473.50, p < 0.05) among the clusters. However, there are no significant differences in map app usage duration (U = 127,387.0, p > 0.05). It suggests that participants tend to have longer overall phone session in low light environment but spend more time on map app per session in strong light condition.

For the tap speed, Figure 23 is the boxplots comparing the general tap speed (number of taps per second) and map app tap speed (map taps per second). The visual difference is not explicit on the boxplots among for both general tap speed (median at 0.44 and 0.40 for Low and Strong Light cluster respectively) and map app tap speed (median at 0.439 and 0.440 for Low and Strong Light cluster respectively). There is no significant difference as checked by the Mann Whitney U test for both general tap speed (U=128,804.0, p-value > 0.05) and map app tap speed (U = 123,786.0, p > 0.05).

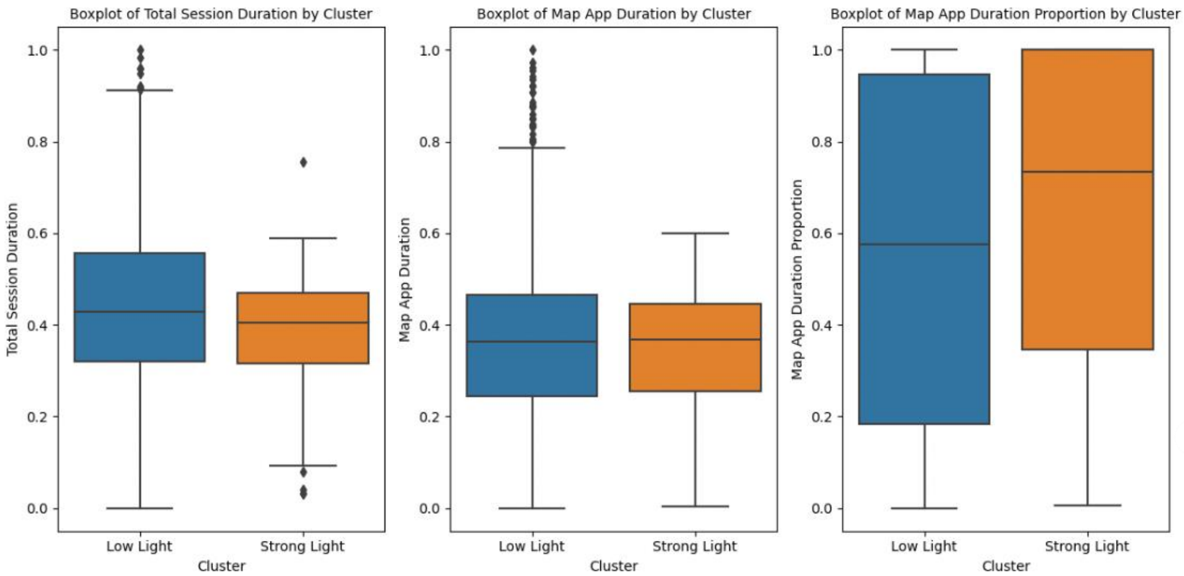


Figure 22. Boxplots of total phone session length, map app usage length and map app length proportion by 2 Lighting Condition Clusters

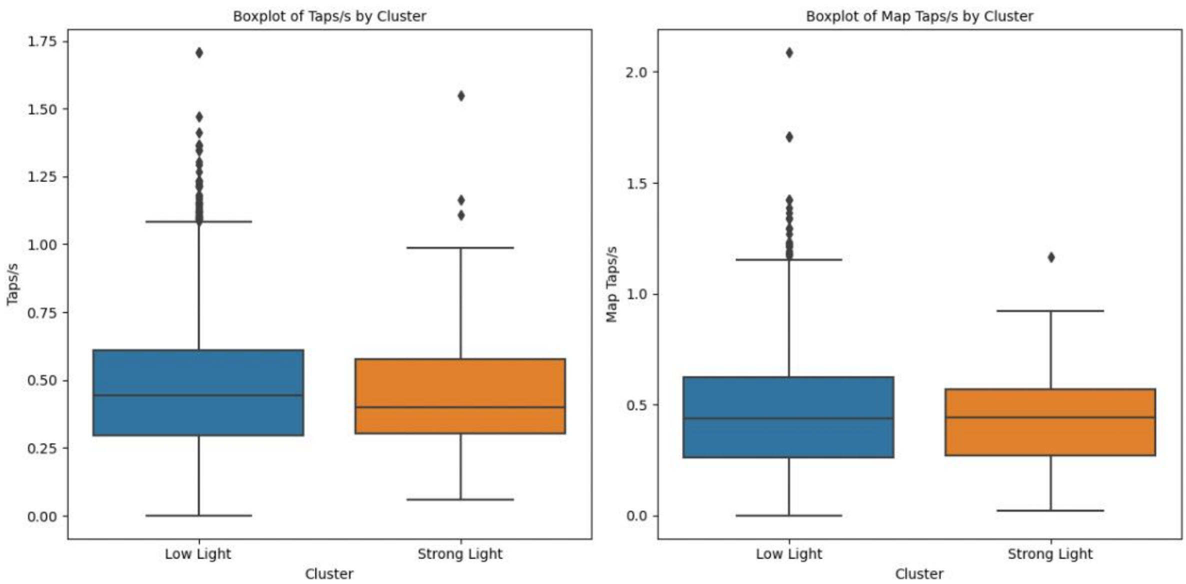


Figure 23. Boxplots of Tap Speed and Map App Tap Speed by 2 Lighting Condition Clusters

4.4.2 In-app Map Usage across 2 lighting condition clusters

Figure 24 is the distribution of all app category tap count of the two clusters. From Figure 10, it is already known that *Communication*, *Travel and Local*, and *Social* are the most used categories in general. In terms of non-map app usage, for *Communication*, Strong Light cluster (49.59%) has higher tap count percentage than Low Light cluster (43.52%); for *Social,* Low Light cluster has profoundly higher usage (12.05%) than Strong Light cluster (1.55%). In terms of Map app usage, for *Travel and Local*, the tap count percentage is dramatically higher in Strong Light (35.27%) than Low Light cluster (17.76%); as for *Maps and Navigation*, the tap count percentage is similar among two clusters with 5.14% in Low Light cluster and 5.06% in Strong Light cluster.

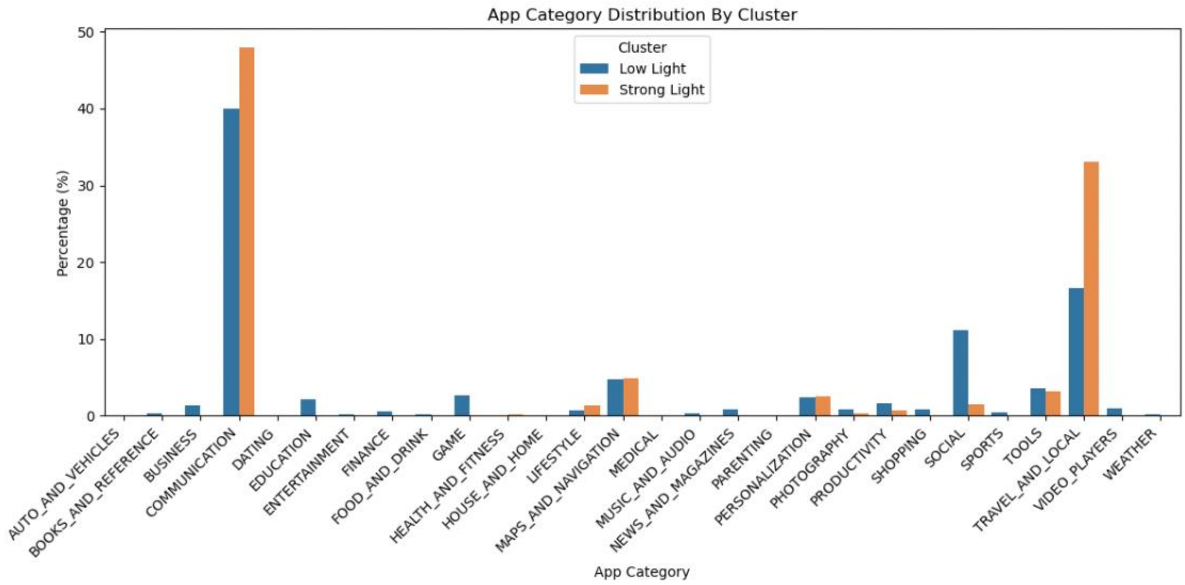


Figure 24. Distribution of all app categories across 2 Lighting Condition Clusters

Figure 25 shows the bar chart of all map app tap counts on a log scale. A total of 11 apps are commonly found across both lighting condition clusters, including *Google Maps, Swisstopo, SBB, SwitzerlandMobility, OpenStreetMap, SNCF train, ENBW mobility, Fairtiq, Limebike, Mobility.ch,* and Flight Radar 24. It is to note that *PeakLens,* an augmented and virtual reality app for mountain information, is found exclusively in the Strong Light Cluster. Since the clusters are derived using K-means clustering algorithm, the number of records in each cluster is imbalanced (2,853 in Low Light clusters vs 85 in Strong Light clusters). Figure 26 and 27 showed the normalised tap count distributions of apps in the *Maps and Navigation* and *Travel and Local* categories respectively.

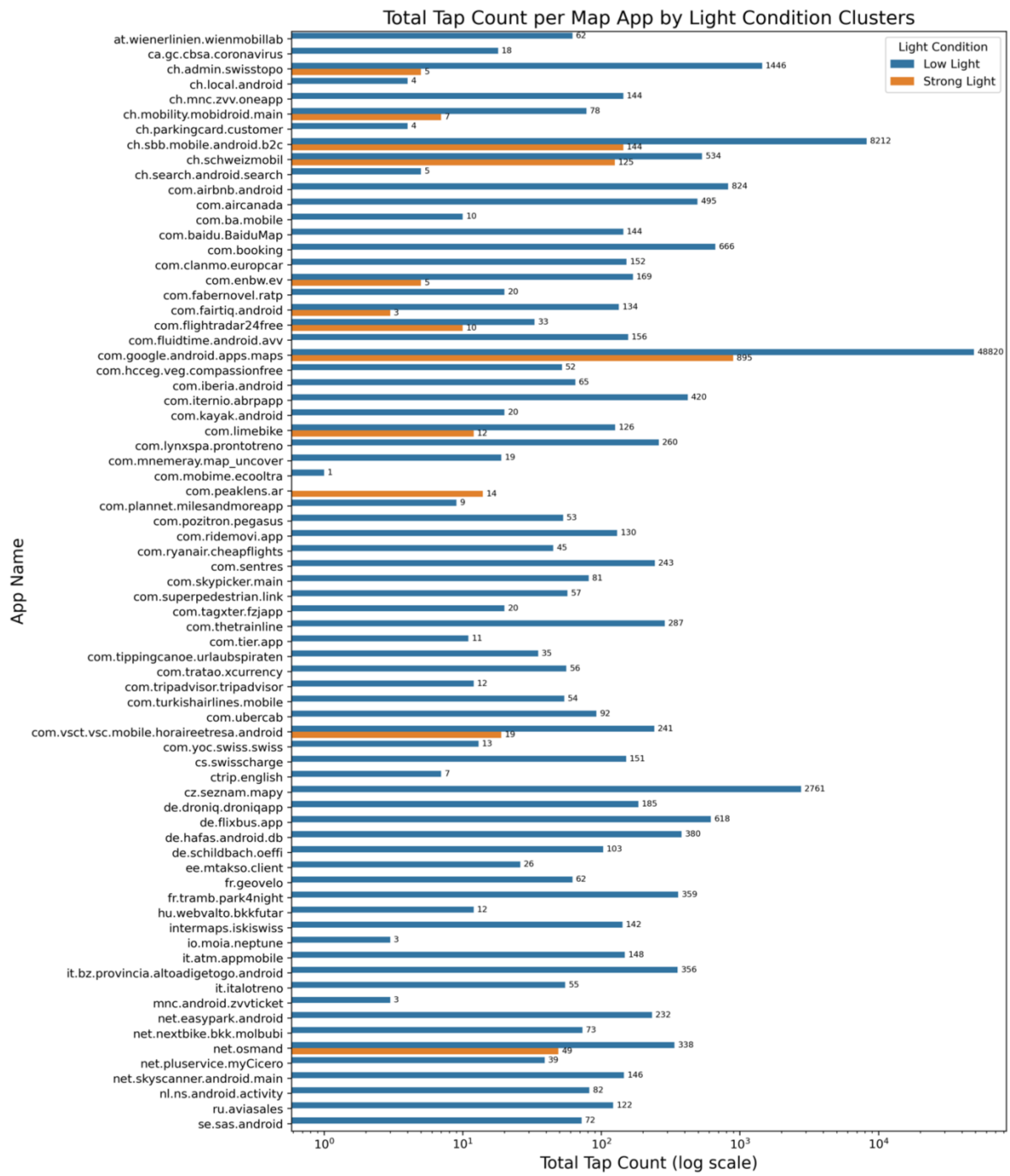


Figure 25. Bar chart of tap count of all map app in 2 Lighting Condition Clusters

In the Strong Light cluster, S*BB Mobile* dominates the Maps and Navigation category, accounting for 87.80% of taps, while other apps such as *Mobility.ch* (4.26%), *Swisstopo* (3.04%), *ENBW Mobility* (an apps showing the free charging points of electric car) (3.04%), and *Fairtiq* (1.82%) show relatively limited use. Google Maps is the dominant app in *Travel and Local* category, though the percentage of total tap count is similar for Low Light cluster (88.34%) and Strong Light cluster (79.62%).

A chi-square test of independence revealed that map app tap count differed significantly across lighting condition clusters for all 11 common apps among both clusters ($p < 0.05$). The strongest associations were observed for Google Maps ($\chi^2 = 46{,}199.45$, $p < 0.001$), SBB Mobile ($\chi^2 = 7{,}789.93$, $p < 0.001$), and Swisstopo ($\chi^2 = 1{,}431.07$, $p < 0.001$), indicating notable shifts in user behaviour depending on light conditions.

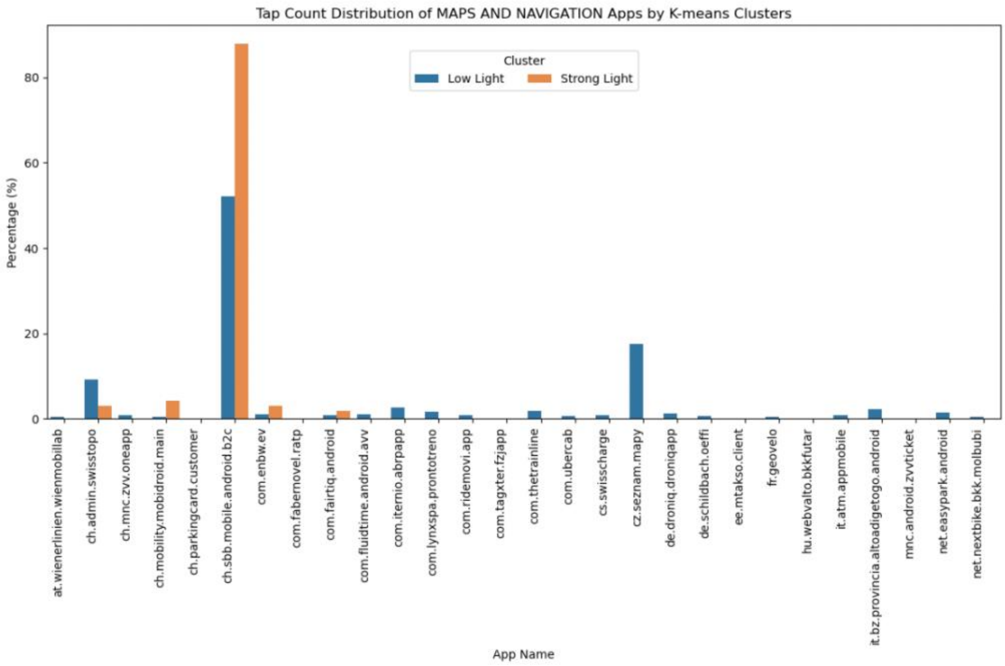


Figure 26. Distribution of apps in the Maps And Navigation category across 2 Lighting Condition Clusters

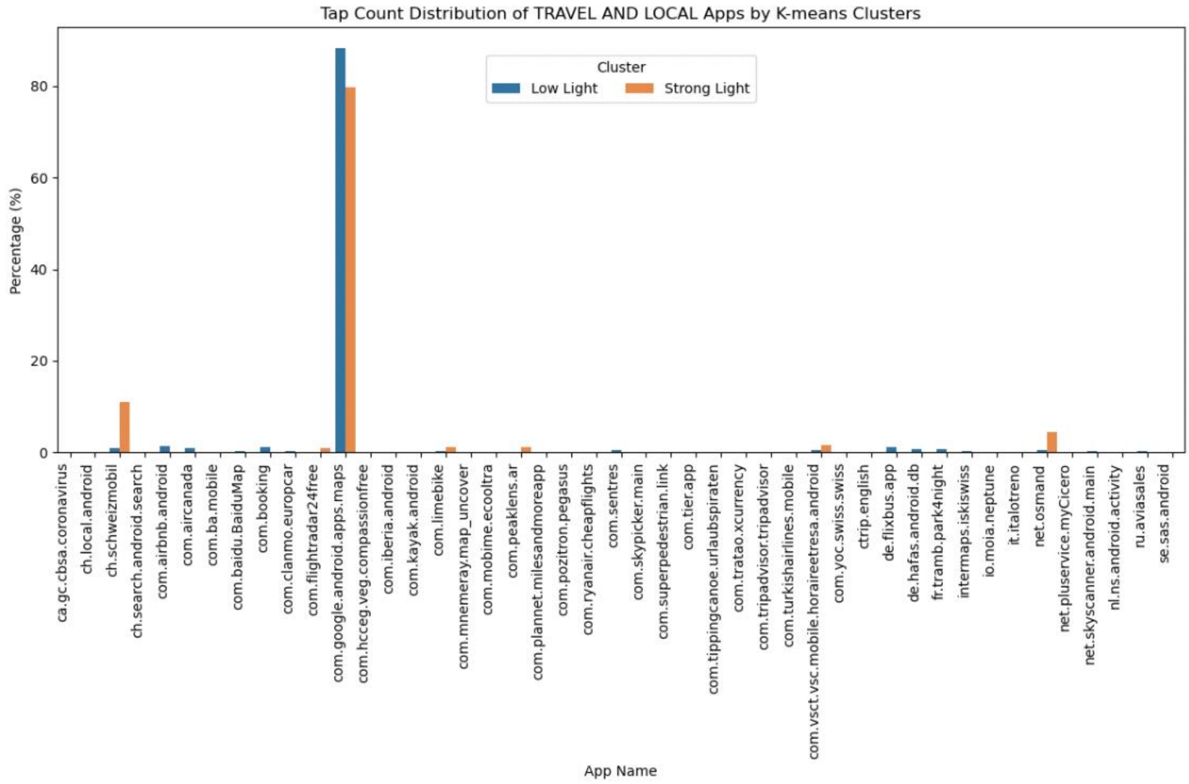


Figure 27. Distribution of apps in the Travel And Local category across 2 Lighting Condition Clusters

The distribution of map app session duration by app name was visualised with boxplots on Figure 28 For better readability, the boxplot on Figure 29 compare the map app duration for the common apps found in both lighting condition clusters. By comparing the median of the boxplot, it is observed the map app session tends to be longer for Strong Light group, such as for *Swisstopo* (median at 0.44 and 0.54 for Low Light and Strong Light respectively), *Mobility.ch* (0.48 vs 0.51), *ENBW mobility* (0.45 vs 0.61), *Fairtiq* (0.47 vs 0.56) and *SNCF Train* (0.43 vs 0.44). However, with the testing of Mann-Whitney U test, significant differences can only be found for *Google Maps*, which median for Low Light cluster is 0.42 (Min: 0, Max: 1, SD: 0.085) and median at 0.43 for Strong Light cluster (Min: 0.049, Max: 0.75, SD: 0.08) (U-statistics: 18,297,774.5, p-value < 0.001) and *ENBW mobility*, which median for Low Light cluster is 0.45 (Min: 0.34, Max: 0.77, SD: 0.06) and median at 0.61 for Strong Light cluster (Min: 0.53, Max: 0.68, SD: 0.07) (U-statistic: 37, p-value < 0.01). In terms of session duration by map app level, significant different in session duration can be seen in different lighting condition clusters in specific map apps.

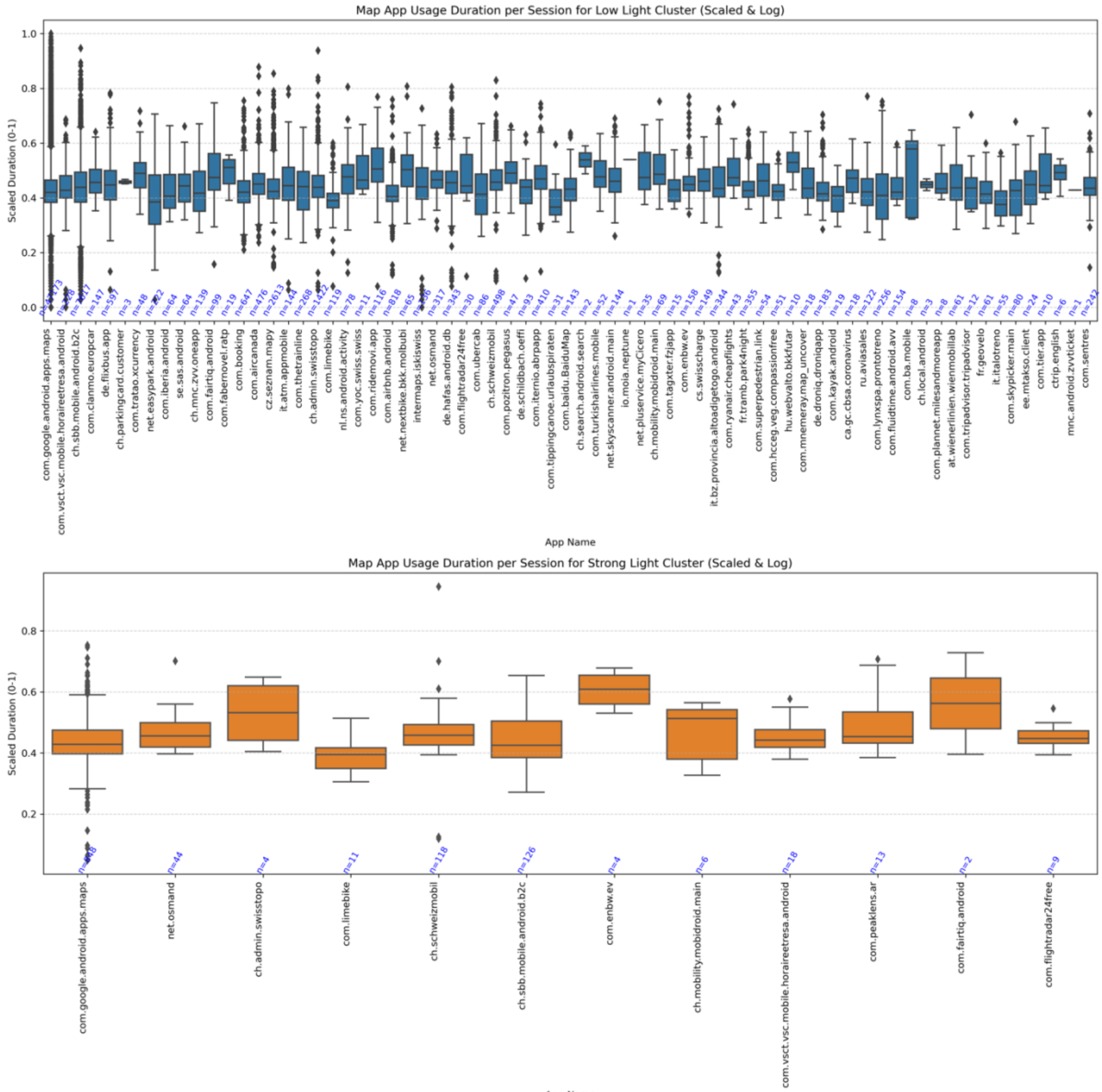


Figure 28. Boxplots of map app usage duration across 2 lighting condition clusters

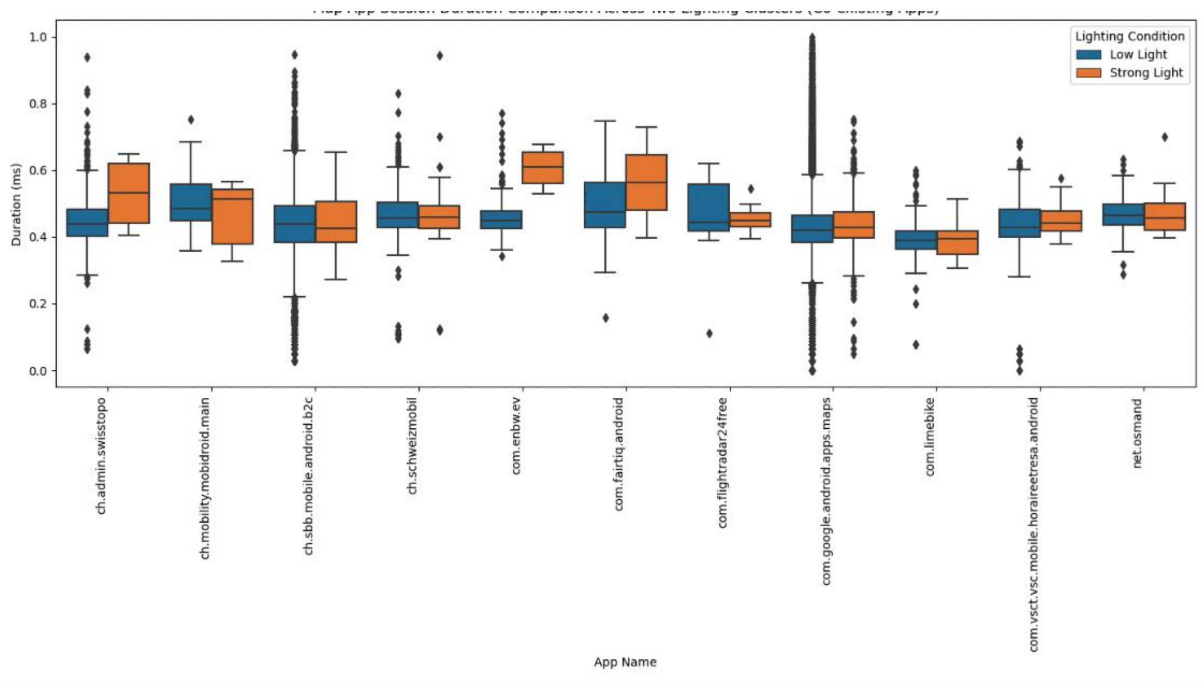


Figure 29. Boxplots of map app usage duration across 2 lighting condition clusters (only common apps)

The distribution of map app tap speed by app name in two lighting conditions was visualised with boxplots on Figure 30. For better readability, the boxplot on Figure 31 compares the map app tap speed (taps/s) for the common apps found in both lighting condition clusters. By comparing the median of the boxplot, tap speed tends to be slower for Strong Light group, such as for *Swisstopo* and *Switzerland Mobility*. However, with the statistical result of Mann-Whitney U test, no significant result can be found in among the 11 common apps ($p > 0.05$). Thus, in terms of tap speed by map app level, there is no significant different in tap speed in different lighting condition clusters.

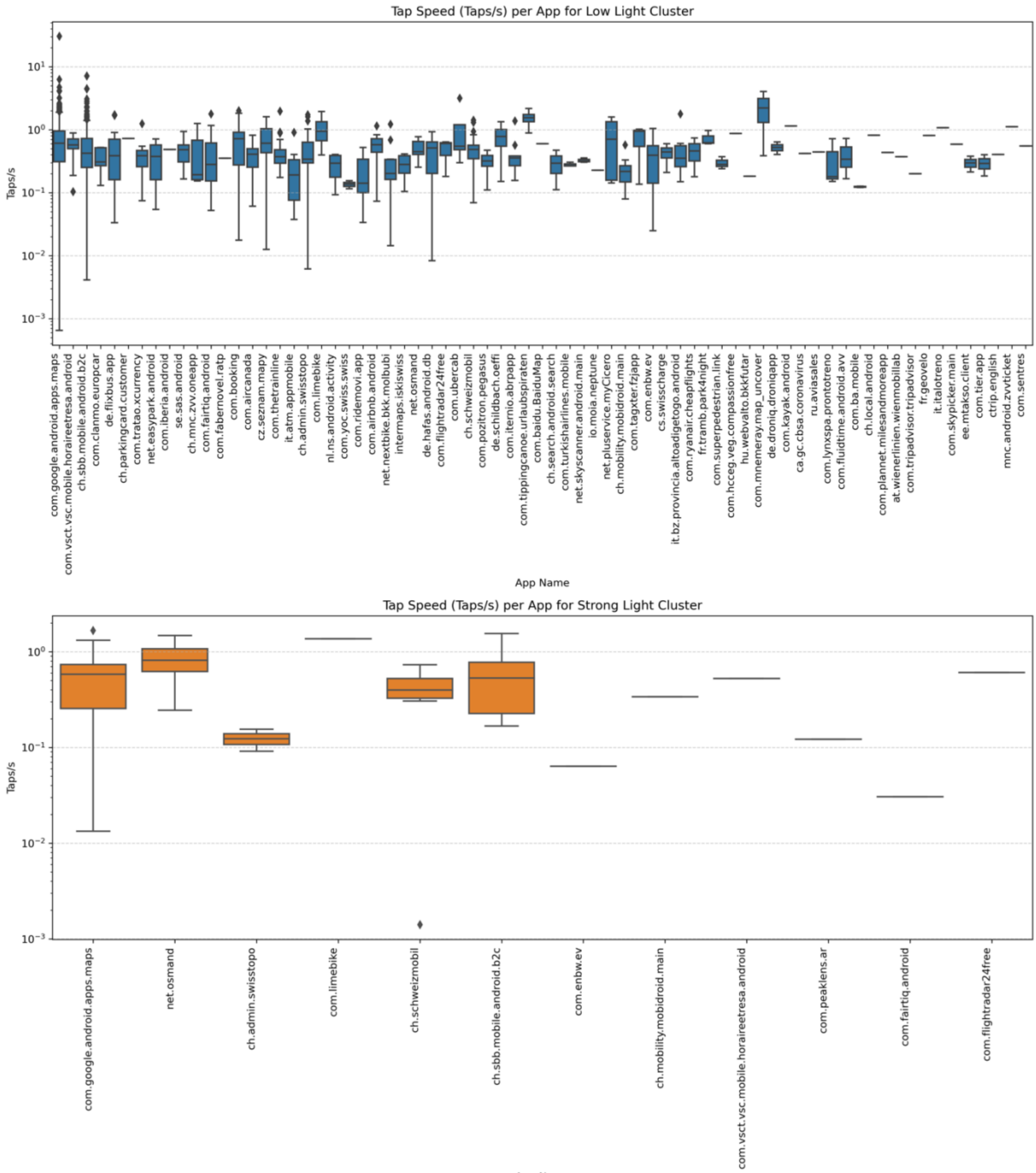


Figure 30. Boxplots of map app tap speed across 2 lighting condition clusters

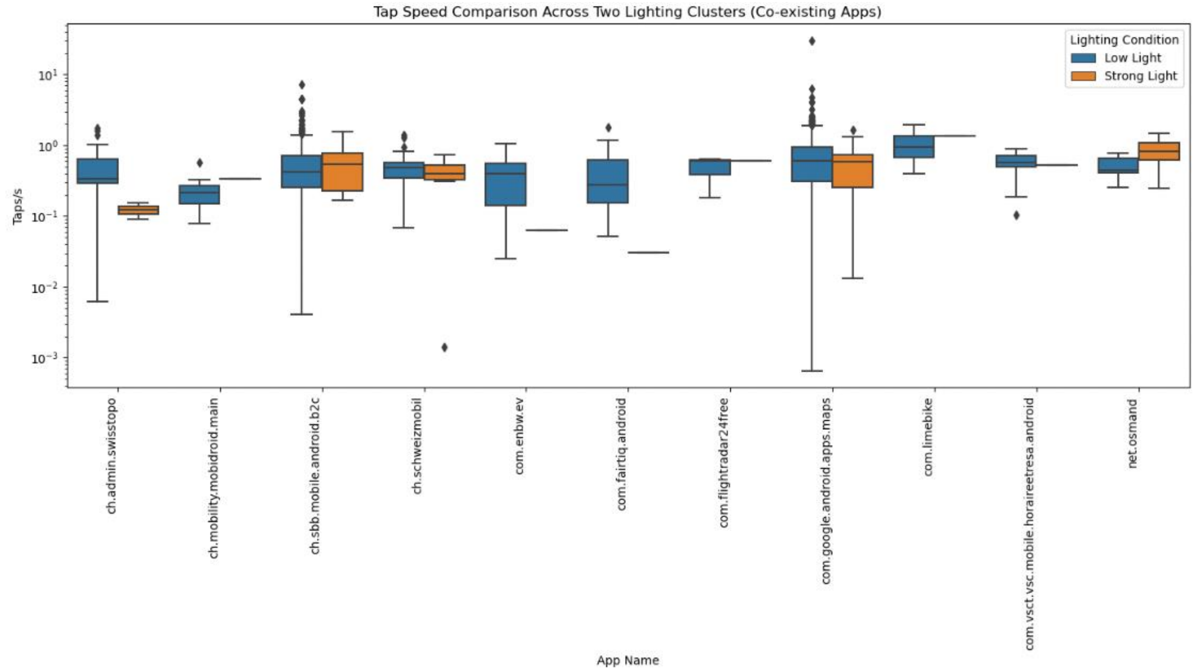


Figure 31. Boxplots of map app tap speed across 2 lighting condition clusters (only common apps)

4.5 Map App Usage by time of the day

4.5.1 General Map App Usage across time of day groups

Four time groups, Morning, Afternoon, Evening, and Night, are assigned based on the mode of the hour of phone session. Among the 2,938 phone sessions, there are 863 sessions used in Morning, 1,325 in the Afternoon, 637 in Evening group and 113 in Night groups.

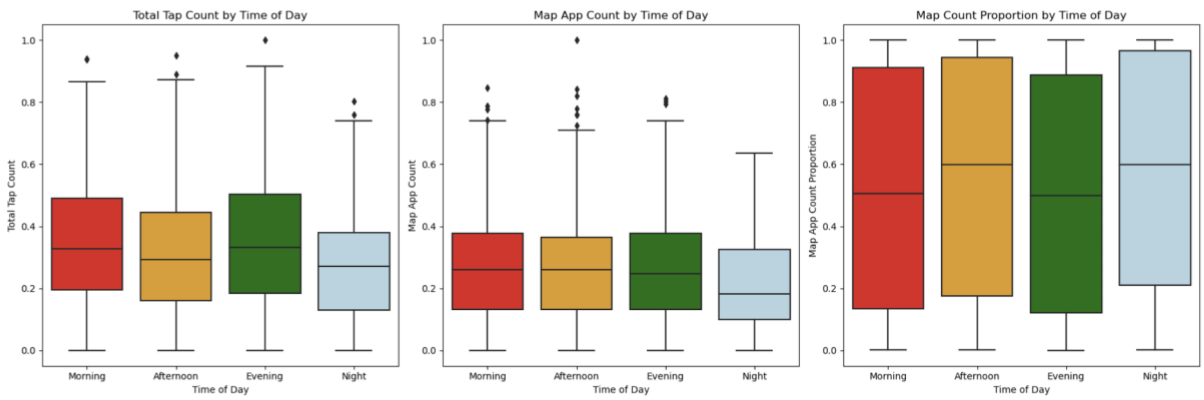


Figure 32. Boxplots of tap count variables across different time of day

Figure 32 presents boxplots comparing the total tap count, map app count, and map app tap count proportion across the 4 time groups. To statistically assess differences between clusters, a Kruskal-Wallis test was conducted for each variable.

The median total tap count is higher in the Morning (Median = 0.3270, Min = 0, Max = 0.94, SD = 0.20) and Evening group (Median = 0.3308, Min = 0, Max = 1, SD = 0.20) compared to the Afternoon (Median = 0.2925, Min = 0, Max = 0.95, SD = 0.19) and Night groups (Median = 0.2712, Min = 0, Max = 0.80, SD = 0.18). The median of map app tap count is more average and have higher usage for Morning (Median = 0.2592, Min = 0, Max = 0.84, SD = 0.16), Afternoon (Median = 0.2592, Min = 0, Max = 1, SD = 0.16) and Evening (Median = 0.2466, Min = 0, Max = 0.81, SD = 0.17) than the Night group (Median = 0.1812, Min = 0, Max = 0.64, SD = 0.15). For the map app tap count proportion, by comparing the median, the usage is higher for the Afternoon (Median = 0.5998, Min = 0, Max = 0.81, SD = 0.17) and Night group (Median = 0.5998, Min = 0, Max = 0.81, SD = 0.17) than the Morning (Median = 0.5047, Min = 0, Max = 0.81, SD = 0.17) and Evening group (Median = 0.4998, Min = 0, Max = 0.81, SD = 0.17).

These observations were supported by the Kruskal-Wallis test. They are all significant different among the tap count-related variables among the four time groups. For total tap count, the H-statistics is 23.85 (p-value < 0.001); for map app count, the H-statistics is 9.47 (p-value < 0.05); and for map app count proportion, the H-statistics is 13.20 (p-value < 0.05). The overall tap count is more frequent in morning and evening, map app tap count is generally higher from morning to evening, and the map count proportion is highest in the afternoon, followed by night.

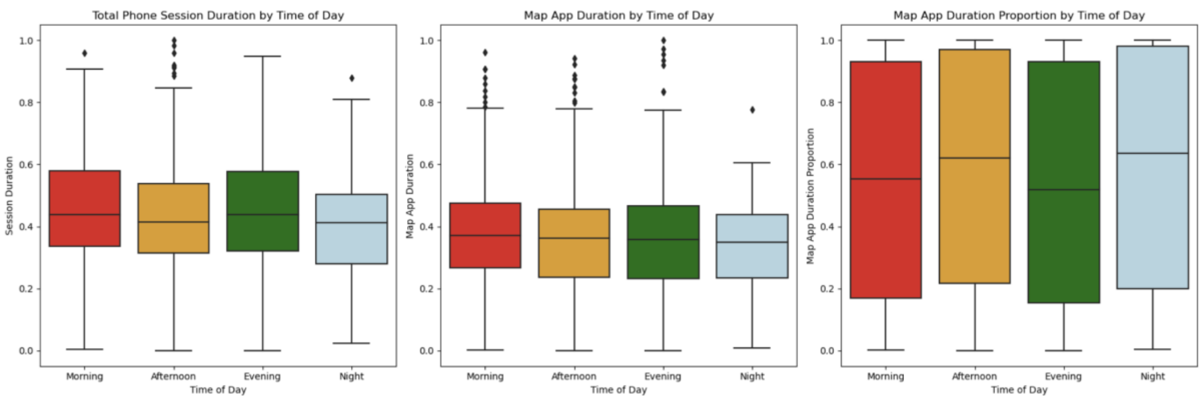


Figure 33. Boxplots of phone session duration variables across different time of day

Figure 33 presents boxplots comparing the total session duration, map app duration, and map app duration proportion across the four time-of-day groups. Similar to the tap count results, the median general phone session duration is longer in the Morning (Median = 0.4392, Min = 0.0040, Max = 0.96, SD = 0.18) and Evening groups (Median = 0.4381, Min = 0, Max = 0.95, SD = 0.19), compared to the Afternoon (Median = 0.4148, Min = 0, Max = 1, SD = 0.17) and Night groups (Median = 0.4126, Min = 0.022, Max = 0.88, SD = 0.17). Map app duration appears more balanced across groups, with slightly higher median usage in the Morning (Median = 0.3705, Min = 0.00046, Max = 0.96, SD = 0.17), Afternoon (Median = 0.3619, Min = 0.00034, Max = 0.94, SD = 0.16), and Evening (Median = 0.3587, Min = 0, Max = 1, SD = 0.18) than in the Night group (Median = 0.3494, Min = 0.0073, Max = 0.77, SD = 0.15). For the map app duration proportion, the Afternoon (Median = 0.6198, Min = 0.00005, Max = 1, SD = 0.37) and Night groups (Median = 0.6350, Min = 0.004, Max = 1, SD = 0.37) show higher usage compared to the Morning (Median = 0.5536, Min = 0.0007, Max = 1, SD = 0.37) and Evening groups (Median = 0.5188, Min = 0, Max = 1, SD = 0.37).

Kruskal-Wallis tests confirmed that all session duration-related variables significant differ among the four time groups. For total phone session duration, the H-statistics is 21.89 (p-value < 0.001); for map app duration the H-statistics is 8.46 (p-value < 0.05); and for map app duration proportion, the H-statistics is 13.77 (p-value < 0.01). These results follow a similar pattern to the tap count analysis: phone sessions tend to be longer in the morning and evening, map app durations are relatively stable from morning to evening, and the highest proportional use of map apps occurs in the afternoon, followed by the night.

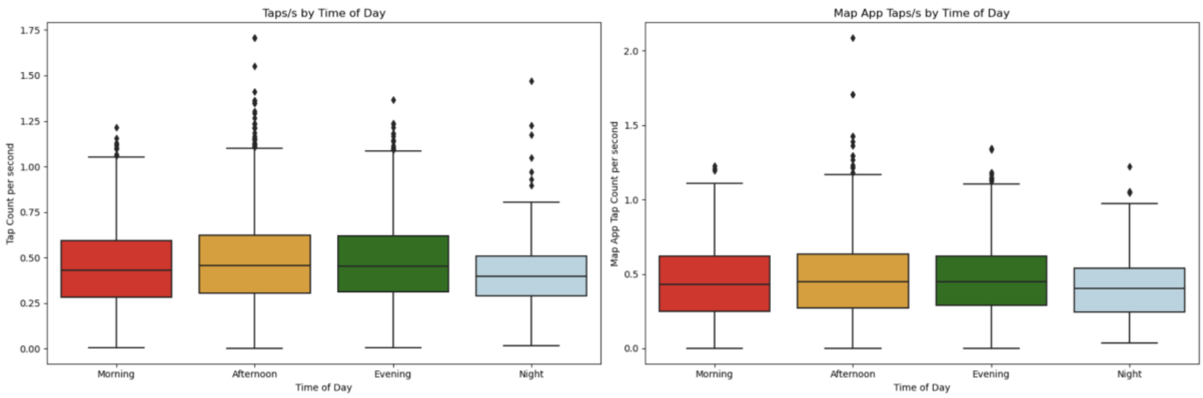


Figure 34. Boxplots of tap speed variables across different time of day

Figure 34 presents boxplots comparing general tap speed and map app tap speed across the four time-of-day groups. General tap speed appears to be faster during the daytime. The median tap speed in the Morning is 0.43 (Min: 0.0048, Max: 1.22, SD: 0.24), in the Afternoon 0.46 (Min: 0.0013, Max: 1.71, SD: 0.26), and in the Evening 0.45 (Min: 0.0045, Max: 1.36, SD: 0.25), while the Night group shows a slower median of 0.40 (Min: 0.016, Max: 1.47, SD: 0.23). For map app tap speed, the distribution is more consistent across time groups, with median values of 0.43 (Morning), 0.45 (Afternoon), 0.45 (Evening), and 0.40 (Night). A Kruskal-Wallis test revealed a significant difference in general tap speed across time groups (H = 12.34, $p < 0.01$), while no significant difference was found in map app tap speed (H = 7.45, $p > 0.05$).

4.5.2 In-app Map Usage across time of day groups

Figure 35 illustrates the tap count of each map app across different times of day, Figure 36 and 37 show the distribution of map apps in different time of day in Map and Navigation and *Travel and Local* category respectively. Only seven apps are used across all four time groups: *Swisstopo, SBB Mobile, Air Canada, Booking.com, Fairtiq, Google Maps, and DB Train.*

Most apps show higher usage during the daytime (Morning and Afternoon), such as *Swisstopo* (15.7% Morning, 6.2% Afternoon), *SBB Mobile* (35.1% Morning, 54.2% Afternoon), *Google Maps* (assumed high daytime use, though not shown in current snippet), *Switzerland Mobility*, *Booking.com, DB Train, Flixbus, and Baidu Maps*. Some apps are exclusively used during the day, including *ZVV* (0.80% Morning, 1.48% Afternoon), *Mapy* (23.2% Morning, 21.3% Afternoon), *Mobility.ch* (1.33% Morning, 0.11% Afternoon), *OpenStreetMap, Trenitalia* (4.4% Morning), *Limebike, PeakLens, British Airways, Wiener Linien* (0.95% Afternoon), *Fluidtime* (2.38% Afternoon), and *Parking Card* (0.07% Morning). On the other hand, several apps show more frequent usage during the evening and night, such as *Uber* (3.0% Evening), *Iskiswiss, MyCicero* (4.0% Evening), *Skyscanner, and Scandinavian Airlines*. Some apps appear to be used only at night, such as *TripAdvisor, Airbnb, Geovelo* (2.1% Evening), and the *CBSA Coronavirus* app.

According to a Chi-square test, significant differences in tap count across the four time groups were found for the following six apps: *SBB mobile* (χ^2 = = 2,434.76, p < 0.001), *Google Maps* (χ^2 = 20,094.87, p <0.001), *Swisstopo* (χ^2 = 1,382.72, p < 0.001), *Booking.com* (χ^2 = 352.50, p < 0.001), *Air Canada* (χ^2 =290.38, p < 0.001), *DB Train* (χ^2 =286.06, p < 0.001). These results indicate strong associations between time of day and app usage for these specific apps.

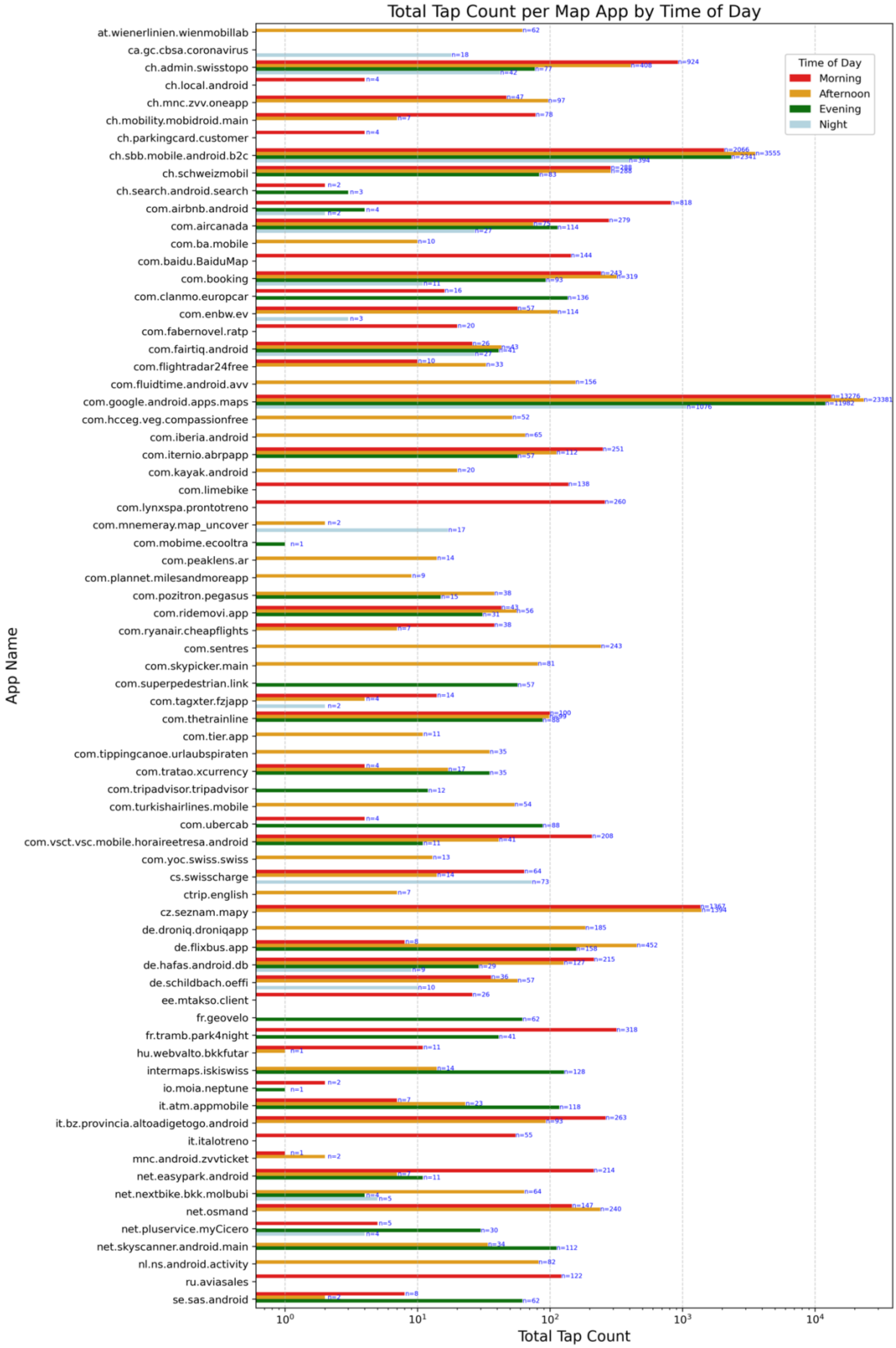


Figure 35. Bar chart of map app count by time of day

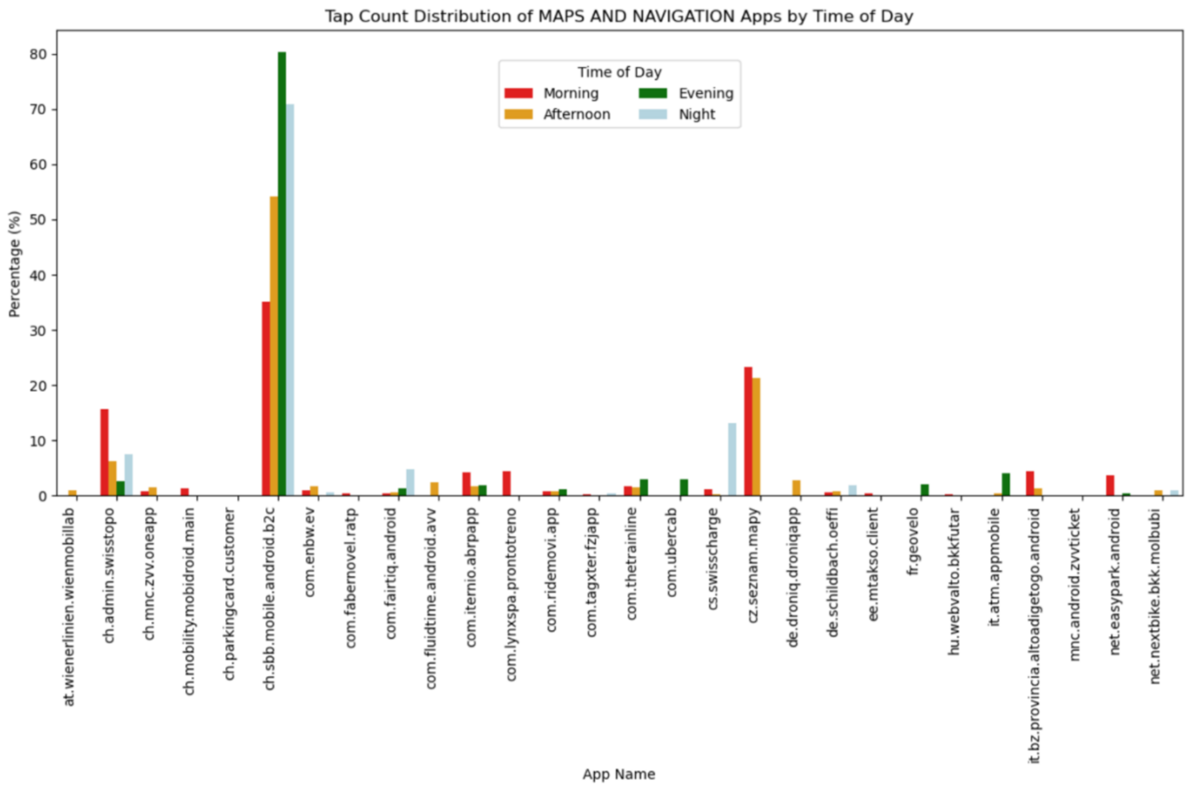


Figure 36. Distribution of apps in the Maps And Navigation category across 4 time group

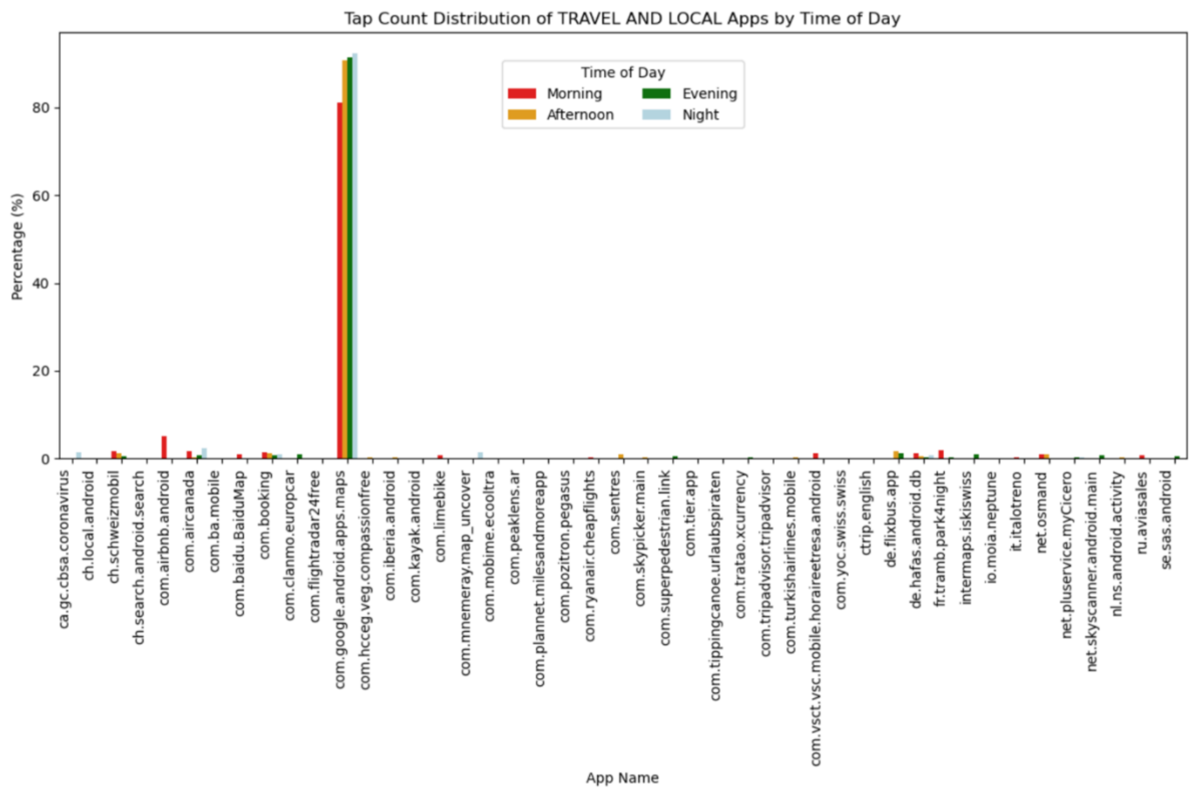


Figure 37. Distribution of apps in the Travel and Local category across 4 time groups

Figure 38 illustrates the session duration of each map app across different times of day and Figure 39 shows the comparison in session duration of those seven common used apps among the four time groups. For some apps, the session duration appeared to be shorter at night, such as *Swisstopo* (median at 0.43, 0.45, 0.44, 0.42 respectively for Morning, Afternoon, Evening, Night) and *Air Canada* (median at 0.4504, 0.440, 0.518, 0.4371). While some apps seems to have longer usage at night, such as *Booking.com* (median at 0.43, 0.41, 0.46, 0.48) and *Fairtiq* (median at 0.47, 0.48, 0.47, 0.53). Significant differences in map app duration through Kruskal-Wallis test could only been found for *Google Maps* (H-statistic = 259.34 , $p < 0.001$), *SBB mobile* (H-statistic = 124.69 , $p < 0.001$), *Booking.com* (H-statistic = 51.85 , $p < 0.001$), *Swisstopo* (H-statistic = 11.36 , $p < 0.01$), and *DB train* (H-statistic = 11.28, $p < 0.05$). No significant difference was found for *Air Canada* and *Fairtiq* ($p > 0.05$).

Figure 40 illustrates the tap speed of each map app across different times of day and Figure 41 shows the comparison in session duration of those seven common used apps among the four time groups. The tap speed of some apps appeared to be slower at afternoon and evening, such as *Swisstopo* (Median at 0.89, 0.33, 0.45 and 0.51 respectively for Morning, Afternoon, Evening, Night), *Air Canada* (Median at 0.34, 0.07, 0.47, 0.58 respectively for Morning, Afternoon, Evening, Night) and *DB Train* (Median at 0.57, 0.50, 0.14 and 0.68 respectively). While some apps seems to have slower tap speed at night, such as *Fairtiq* (Median at 0.46, 0.23, 0.61 and 0.16 respectively for Morning, Afternoon, Evening, Night) and *SBB* mobile (Median at 0.41, 0.42, 0.46 and 0.33 respectively for Morning, Afternoon, Evening, Night). However, significant differences through Kruskal-Wallis test could only been found for *Google Maps* (H-statistic = 10.39, $p < 0.05$) and *DB train* (H-statistic = 13.88, $p < 0.001$). No significant difference was found for *Swisstopo, Booking.com, Fairtiq, Air Canada and SBB mobile* ($p > 0.05$).

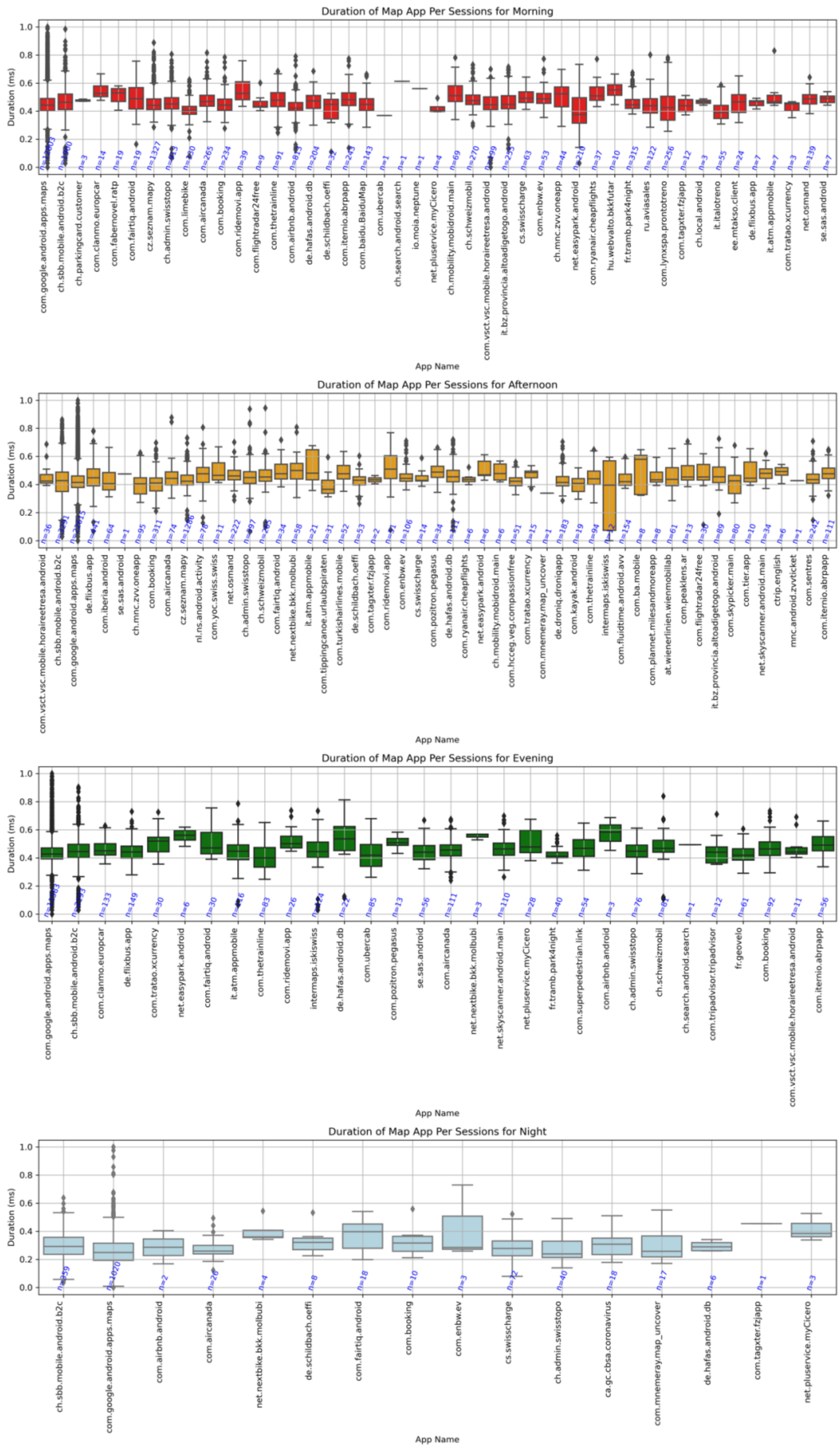


Figure 38. Boxplot of map app duration across different time of day

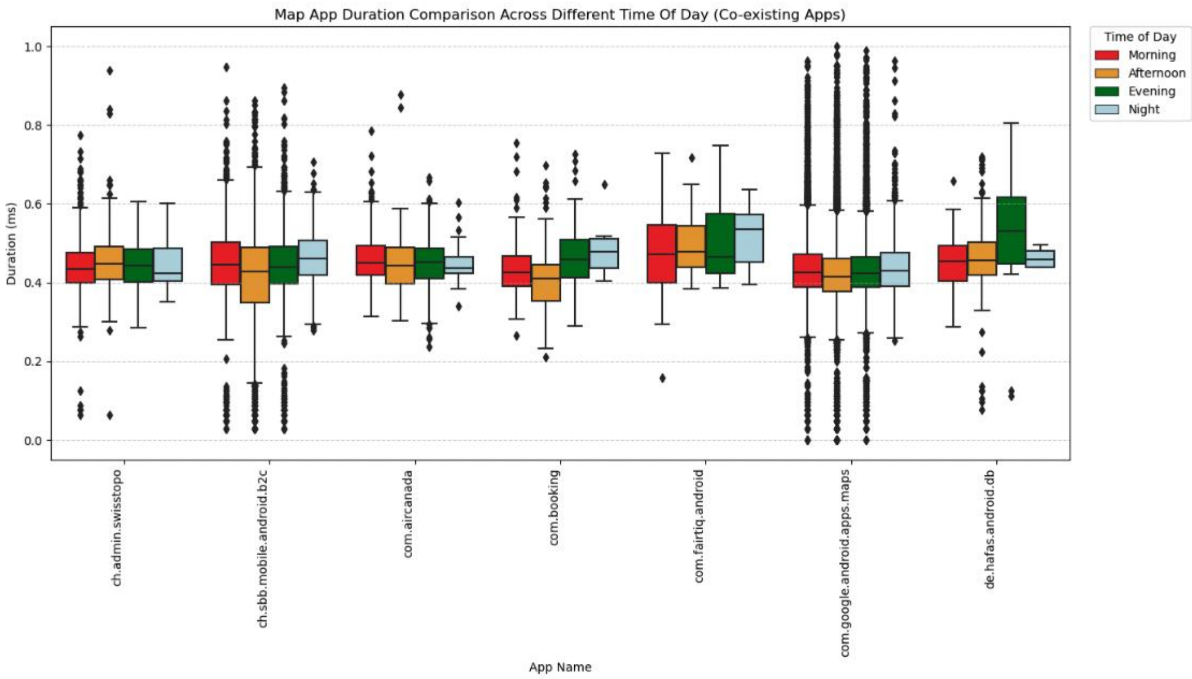


Figure 39. Boxplot of map app duration across different time of day (only common apps)

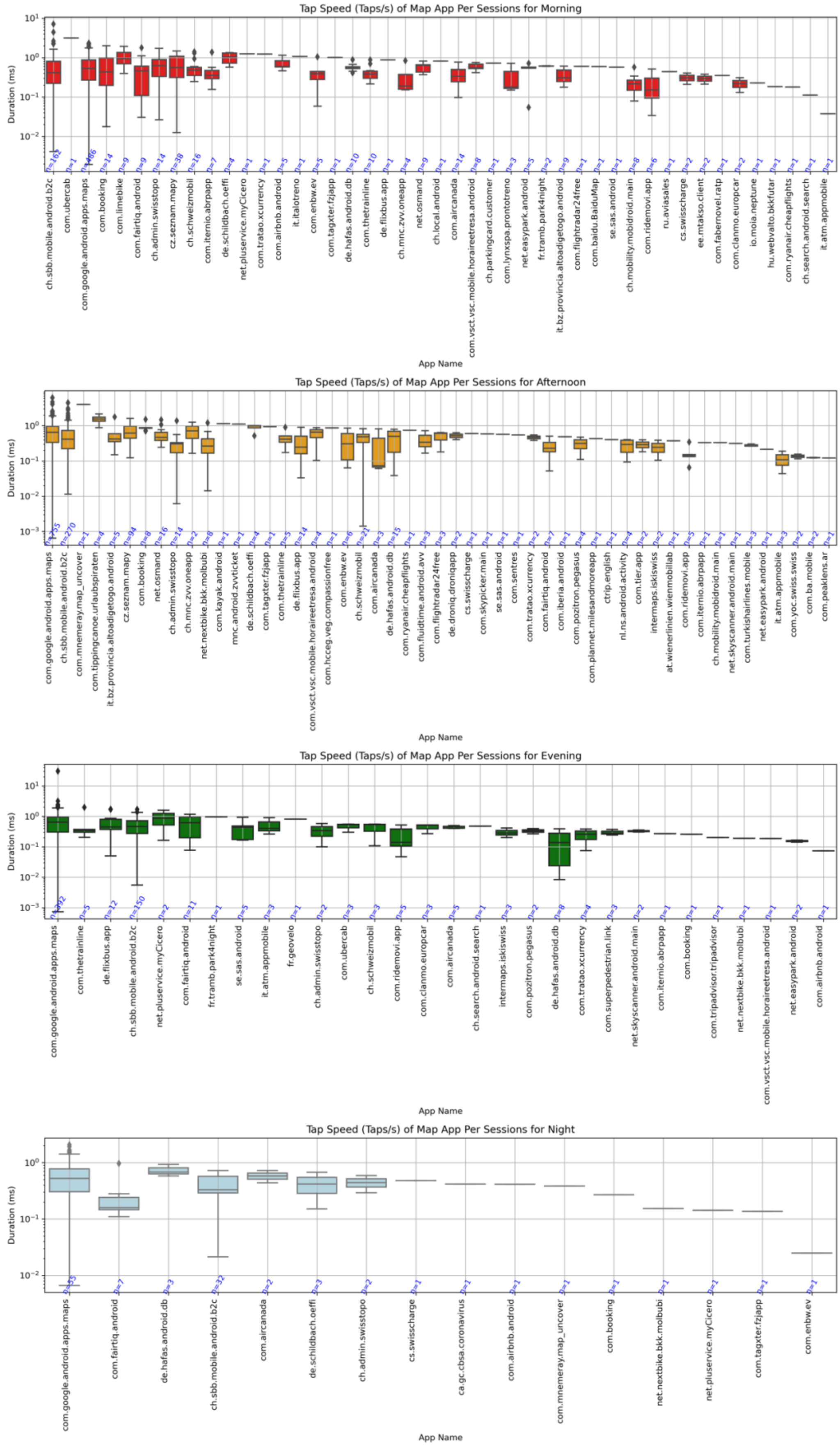


Figure 40. Boxplots of map app tap speed across different time of day

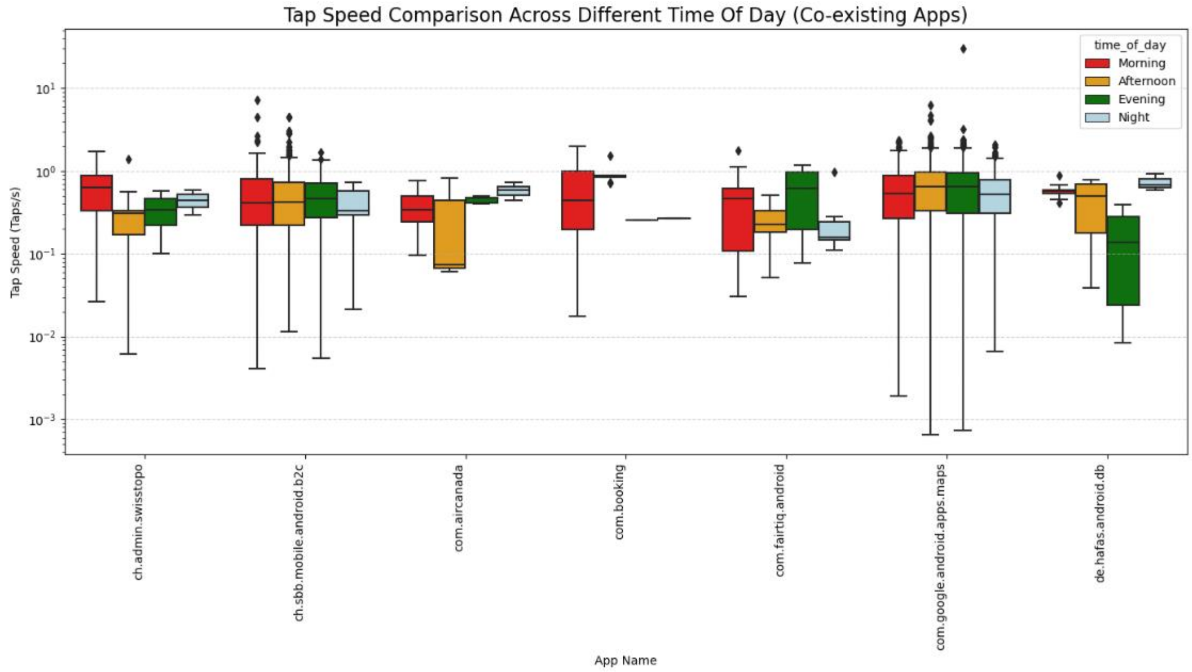


Figure 41. Boxplot of map app tap speed across different time of day (only common apps)

4.6 Light Variation by Indoor/ Outdoor Environment

4.6.1 General Map Usage across 2 environmental states

Among the 1,595 sessions with map app records within Switzerland, based on the function considered both ambient light and building footprints, there are 1,211 outdoors sessions and 384 indoors sessions.

Figure 42 presents boxplots comparing total tap count, map app tap count, and map app tap count proportion across indoor and outdoor environments. For total tap count, the median was slightly higher in the indoor group (Median = 0.34, Min = 0, Max = 1, SD = 0.21) compared to the outdoor group (Median = 0.31, Min = 0, Max = 0.95, SD = 0.20). For map app tap count, the median for the indoor group was 0.26 (Min = 0, Max = 1, SD = 0.19), slightly higher than that of the outdoor group (Median = 0.25, Min = 0, Max = 0.84, SD = 0.16). For map app tap count proportion, the indoor group had a median of 0.48 (Min = 0, Max = 1, SD = 0.37), which was slightly lower than the outdoor group (Median = 0.53, Min = 0.000077, Max = 1, SD = 0.37).

According to the Mann-Whitney U test, a significant difference was found only for total tap count between indoor and outdoor groups (U = 251,625.50, $p < 0.05$). No significant differences were observed for map app tap count or map app tap count proportion ($p > 0.05$).

In terms of tap count across environments, general phone usage appears to be slightly higher indoors, while no significant difference is observed in map app usage between the two environmental states.

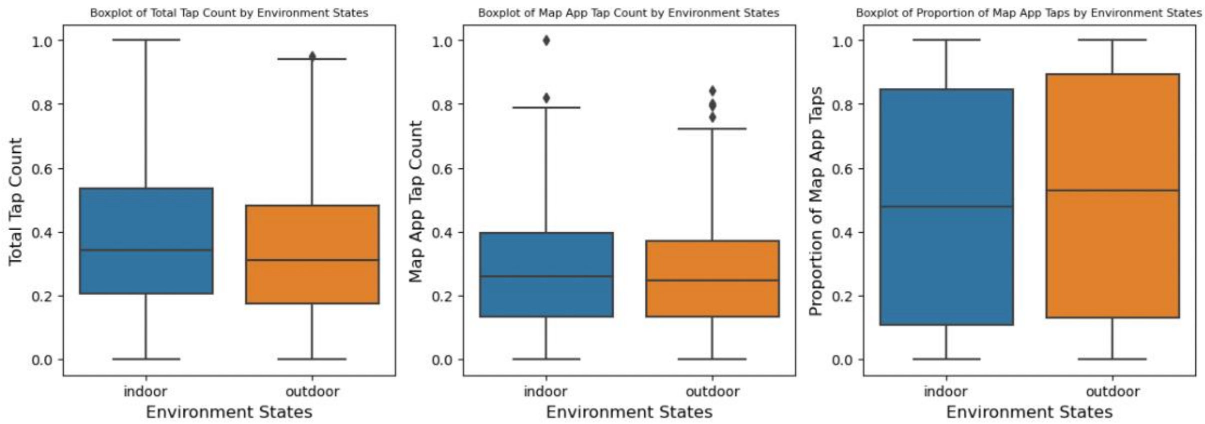


Figure 42. Boxplots of total tap count, map app count and map app tap count proportion across 2 environmental states

Figure 43 presents boxplots comparing phone session length, map app duration, and map app duration proportion across indoor and outdoor environments. For total session duration, the median was slightly higher in the indoor group (Median = 0.46, Min = 0, Max = 0.96, SD = 0.18) compared to the outdoor group (Median = 0.43, Min = 0.0056, Max = 1, SD = 0.18). For map app duration, the median for the indoor group was 0.37 (Min = 0, Max = 0.89, SD = 0.19), slightly longer than that of the outdoor group (Median = 0.36, Min = 0.0009, Max = 1, SD = 0.18). For map app duration proportion, the indoor group had a median of 0.51 (Min = 0.0014, Max = 1, SD = 0.37), which was lower than the outdoor group (Median = 0.60, Min = 0.00001, Max = 1, SD = 0.38).

According to the Mann-Whitney U test, a significant difference was found for total phone session duration (U = 251,998.50, $p < 0.05$) and map app duration proportion (U = 214,198.00, $p < 0.05$) between indoor and outdoor groups. No significant differences were observed for map app duration ($p > 0.05$).

In terms of phone session duration across environments, general phone usage appears to be slightly higher indoors, while the proportion of map app usage is higher in outdoor.

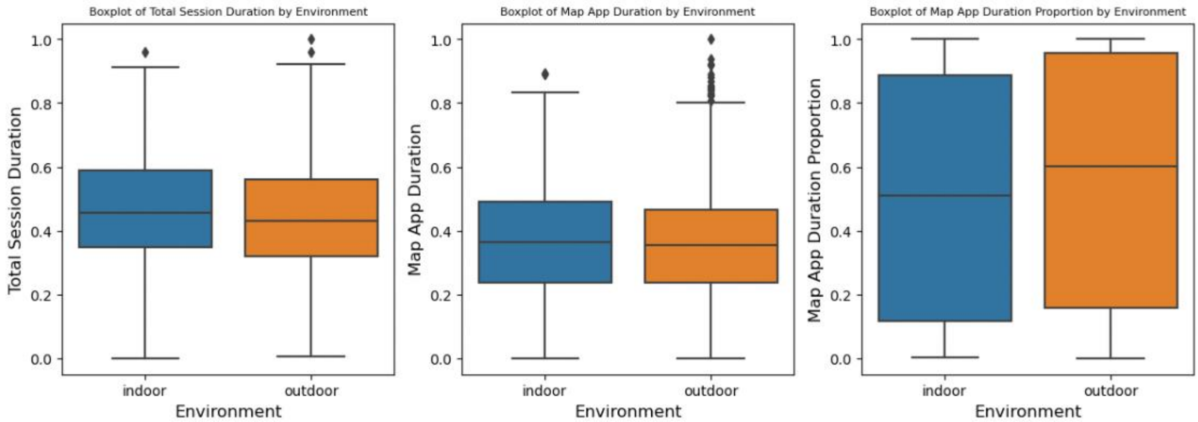


Figure 43. Boxplots of total phone session length, map app usage length and map app length proportion by 2 environmental states

Figure 44 presents boxplots comparing general tap speed and map app tap speed across indoor and outdoor environments. For general tap speed, the median was slightly higher in the outdoor group (Median = 0.43, Min = 0.0048, Max = 1.32, SD = 0.22) compared to the indoor group (Median = 0.42, Min = 0.0012, Max = 1.71, SD = 0.23). For map app tap speed, the median for the indoor group was 0.41 (Min = 0.013, Max = 1.23, SD = 0.26), slower than that of the outdoor group (Median = 0.45, Min = 0.0009, Max = 1.84, SD = 0.28).

However, according to the Mann-Whitney U test, no significant difference was found for both general tap speed (U = 227,732.00, $p > 0.05$) and map app tap speed(U = 226,636.50, $p > 0.05$).

In terms of tap speed across environments, no significant difference is observed in map app usage between the two environmental states.

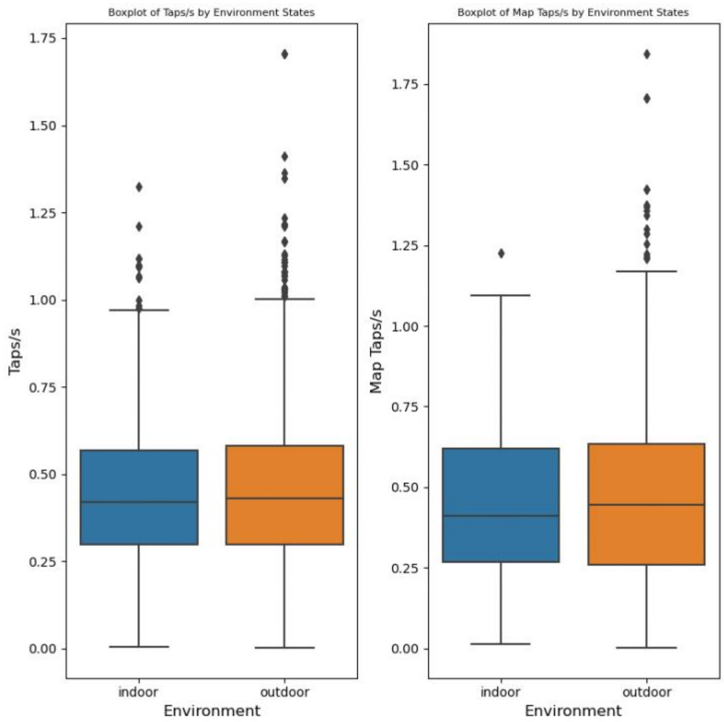


Figure 44. Boxplots of Tap Speed and Map App Tap Speed by 2 environmental states

4.6.2 In-app Map Usage across 2 environmental states

Figure 45 presents a bar chart of overall map app usage across indoor and outdoor environments, while Figures 46 and 47 illustrate the normalized distribution for the *Maps and Navigation* and *Travel and Local* app categories respectively. A total of 23 apps were found to be common between both indoor and outdoor groups, which exceeds the 11 common apps identified via lighting conditions clustering and the 7 identified apps through time-of-day analysis. The most frequently used apps *are Google Maps, SBB Mobile, and Swisstopo.*

Some apps were exclusively used in outdoor environments, such as *OpenStreetMap* (1.9%), *Skypicker* (0.4%), *PeakLens* (0.1%), *SNCF* (0.4%), *Uber* (1.2%), *Tier* (a scooter rental app, 0.1%), *Parking Card* (0.1%), *Air Canada* (0.4%), and *EasyPark* (0.2%). Other apps showed a strong dominance in outdoor usage, including *Flixbus* (2.4% outdoors vs. 0.2% indoors), *SBB Mobile* (86.1% outdoors vs. 51.8% indoors), *Switzerland Mobility* (2.9% vs. 0.7%), *Booking.com* (1.5% vs. 0.2%), *ZVV* (1.7% vs. 0.4%), *Limebike* (0.6% vs. 0.2%), *Iskiswiss* (0.6% vs. 0.1%), and *Oeffi*, a public transport timetable app (1.2% vs. 0.3%).

Conversely, some apps were used exclusively in indoor settings, such as *Baidu Map* (1.4%), *RATP* (Paris public transport, 0.6%), *Kayak* (0.2%), *Fluidtime* (4.8%), *Iberia Airlines* (0.6%), *Geovelo* (1.9%), and *Ctrip* (0.1%). Several apps also demonstrated dominant indoor usage, including *Google Maps* (90.0% indoors vs. 86.3% outdoors), *Swisstopo* (34.3% vs. 4.3%), *Iternio* (3.7% vs. 1.9%), *Park4night* (3.0% vs. 0.2%), and *Pegasus* (0.3% vs. 0.1%).

According to the chi-square test, tap count distributions across indoor and outdoor environments were statistically significant for 18 apps, as summarized in Table 9.

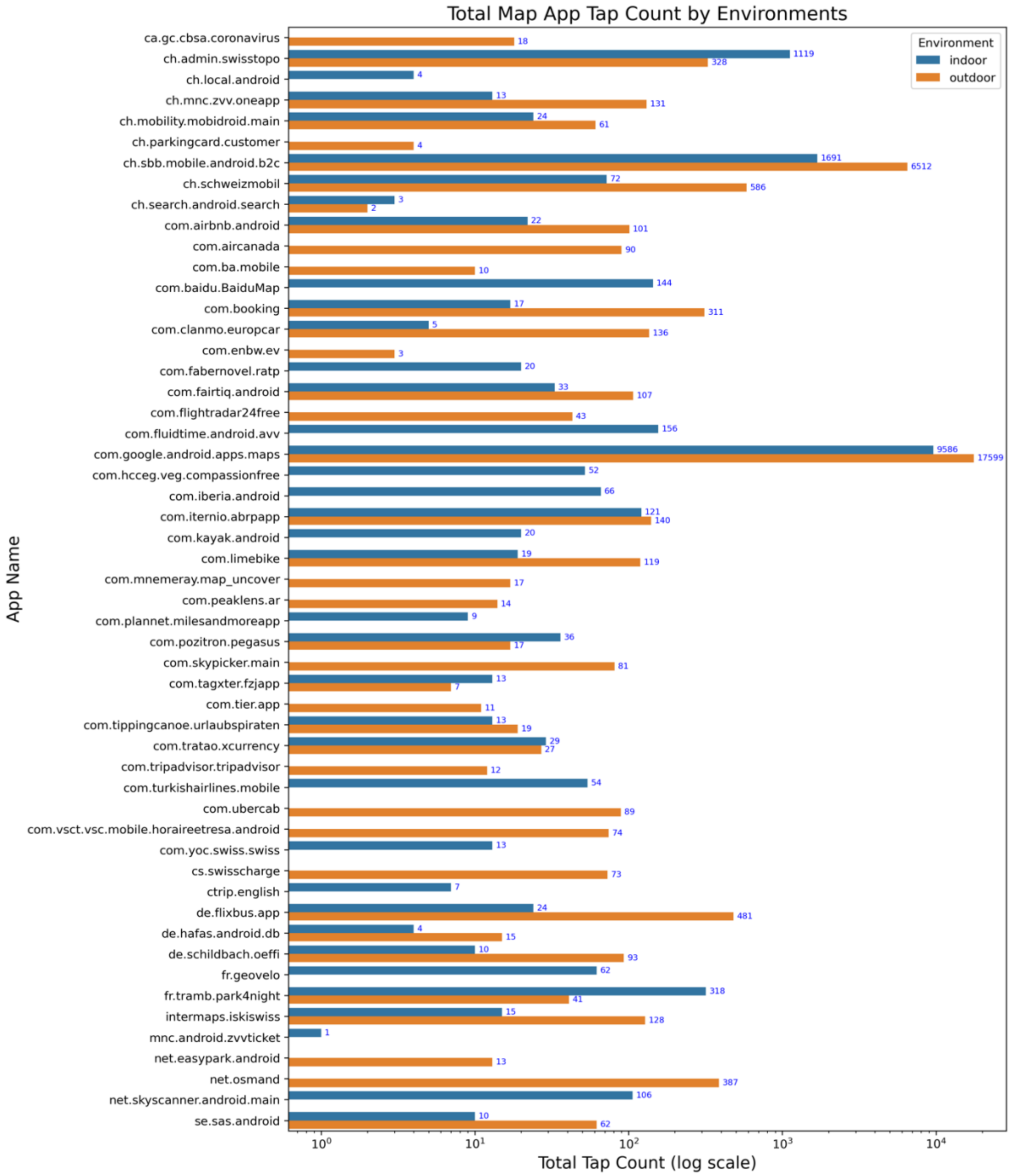


Figure 45. Bar chart of map app counts by 2 environmental states

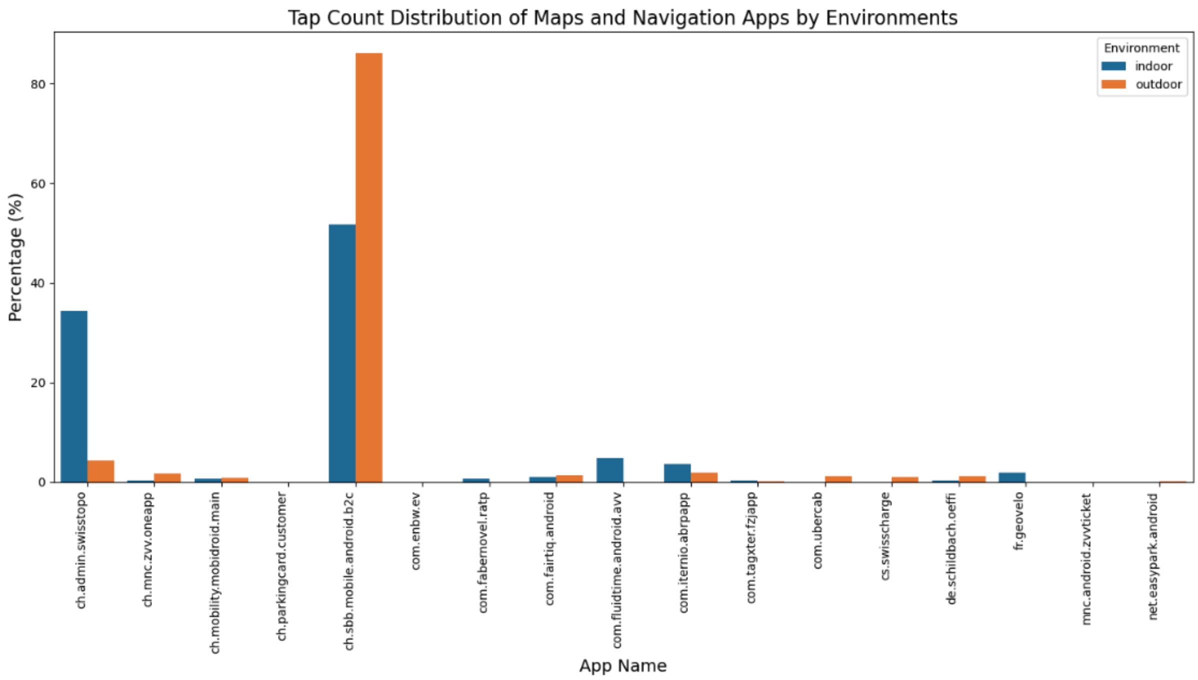


Figure 46. Distribution of apps in the Maps and Navigation category across 2 Environmental states

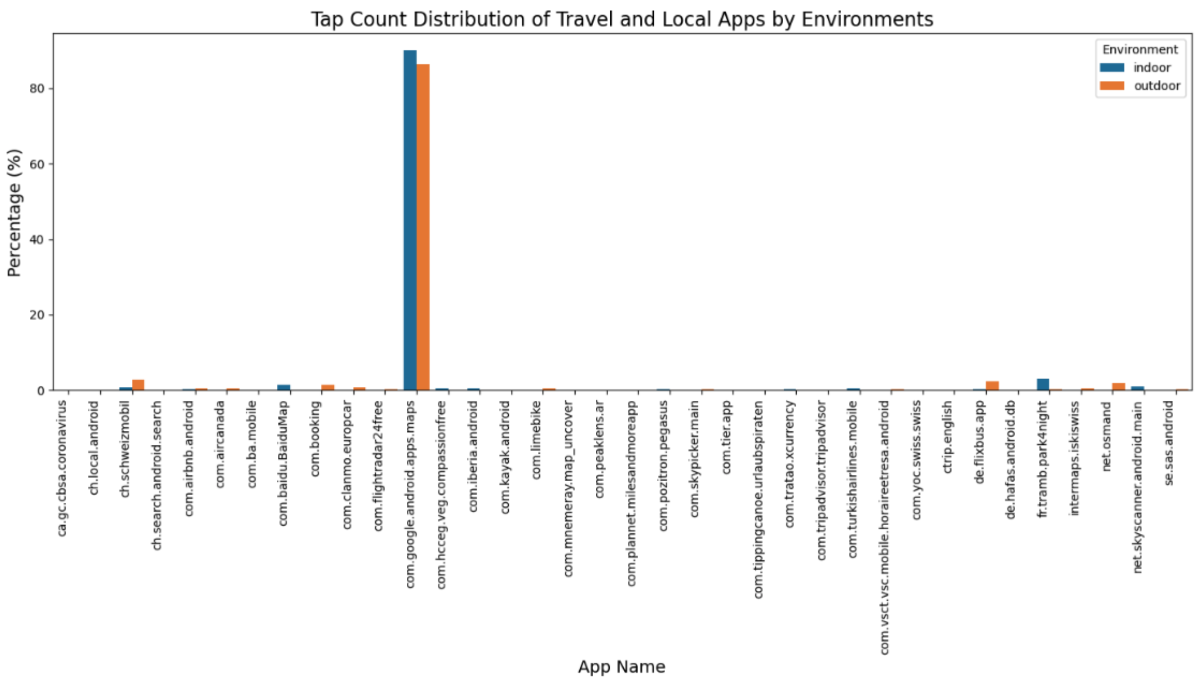


Figure 47. Distribution of apps in the Travel And Local category across 2 Environmental states

	App Name	χ^2	P - value
1	ch.sbb.mobile.android.b2c	2833.358649	<0.001
2	com.google.android.apps.maps	2361.896965	<0.001

3	ch.admin.swisstopo	432.398756	<0.001
4	de.flixbus.app	413.562376	<0.001
5	ch.schweizmobil	401.513678	<0.001
6	com.booking	263.524390	<0.001
7	fr.tramb.park4night	213.729805	<0.001
8	com.clanmo.europcar	121.709220	<0.001
9	ch.mnc.zvv.oneapp	96.694444	<0.001
10	intermaps.iskiswiss	89.293706	<0.001
11	com.limebike	72.463768	<0.001
12	de.schildbach.oeffi	66.883495	<0.001
13	com.airbnb.android	50.739837	<0.001
14	com.fairtiq.android	39.114286	<0.001
15	se.sas.android	37.555556	<0.001
16	ch.mobility.mobidroid.main	16.105882	<0.001
17	com.pozitron.pegasus	6.811321	<0.01
18	de.hafas.android.db	6.368421	< 0.05

Table 9. Chi-square test results for map apps across different environmental conditions

Figure 48 illustrates the scaled session duration of each map app across different environmental states, while Figure 49 compares the scaled session durations for 23 apps that are commonly used in both indoor and outdoor environments. For some apps, session duration appears to be slightly shorter indoors, such as *Swisstopo* (median: 0.43 indoor vs. 0.46 outdoor), *Limebike* (0.38 vs. 0.40), and *Google Maps* (0.41 vs. 0.43). Conversely, certain apps exhibit longer usage sessions indoors, including *ZVV* (0.52 vs. 0.42), *DB Train* (0.50 vs. 0.48), *Iskiswiss* (0.50 vs. 0.44), and *Booking.com* (0.45 vs. 0.59).

The Mann – Whitney U test revealed that 11 out of 23 apps had statistically significant differences in session duration between indoor and outdoor environments. Specifically, *SBB Mobile, Swisstopo, Switzerland Mobility, Flixbus, Booking.com, and Oeffi* all showed highly significant differences with $p < 0.001$. Additionally, *Airbnb, Fairtiq, and Iskiswiss* demonstrated significant differences at $p < 0.01$, while *Mobility.ch* and *Limebike* showed more moderate significance with $p < 0.05$. These findings indicate that, although not all apps vary significantly in usage duration across environments, a subset does exhibit meaningful differences that may relate to contextual or environmental factors influencing app use behaviour.

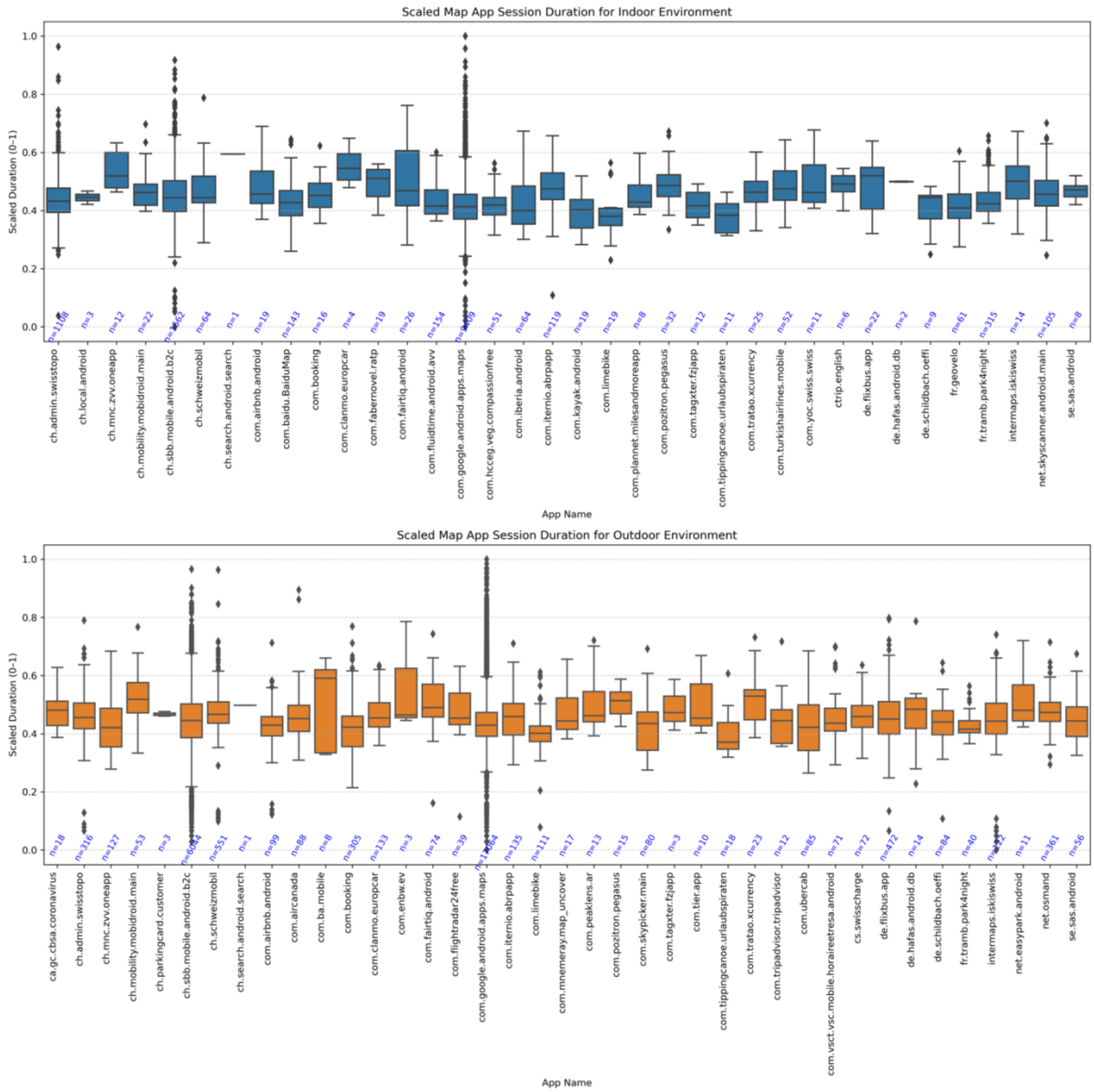


Figure 48. Boxplots of map app duration across different environmental states

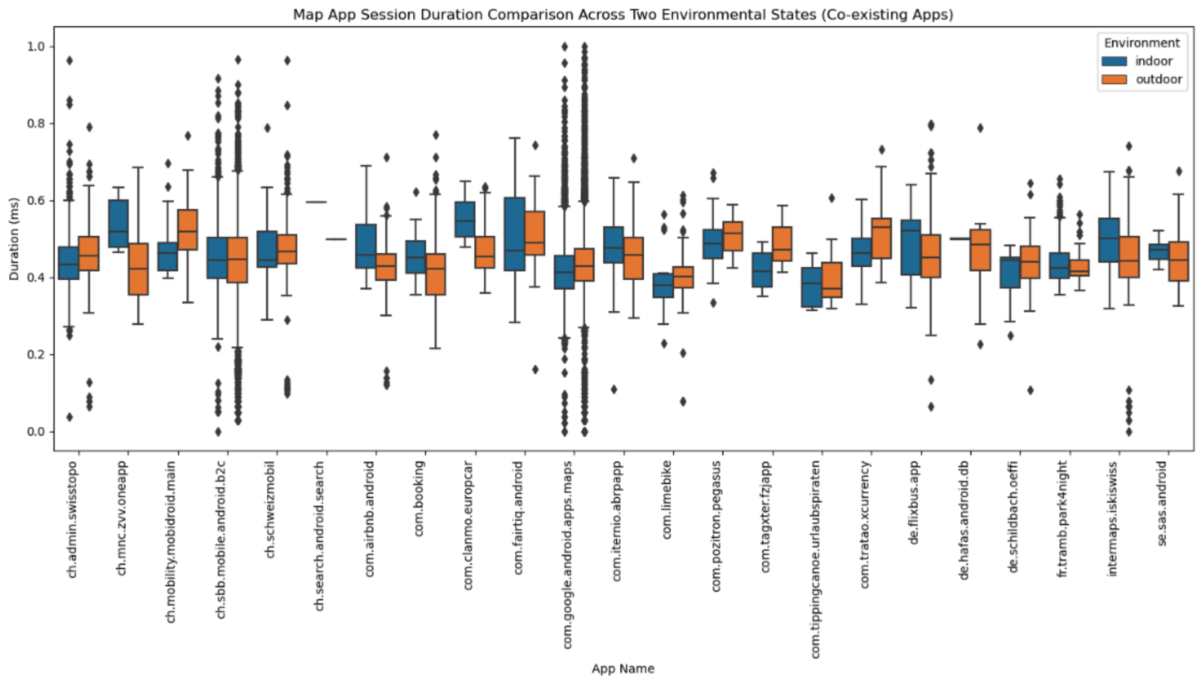


Figure 49. Boxplots of map app duration across different environmental states (common apps)

The distribution of map app tap speed by app name across two environmental conditions was visualized using boxplots in Figure 50. For better readability, Figure 51 compares the tap speed (taps per second) for apps that appear in both the indoor and outdoor groups. By visually inspecting the medians of the boxplots, it is difficult to identify a consistent trend in tap speed. Some apps, such as *Airbnb, SBB Mobile, Switzerland Mobility, and Iternio*, show slower tap speeds indoors, while others, such *as Swisstopo, ZVV, Flixbus, Fairtiq, and Tratao*, appear to have faster indoor tap speeds. However, based on the statistical results from the Mann–Whitney U test, no significant differences were found among the 23 common apps ($p > 0.05$). Therefore, in terms of the individual map app level, tap speed does not significantly differ between indoor and outdoor environments.

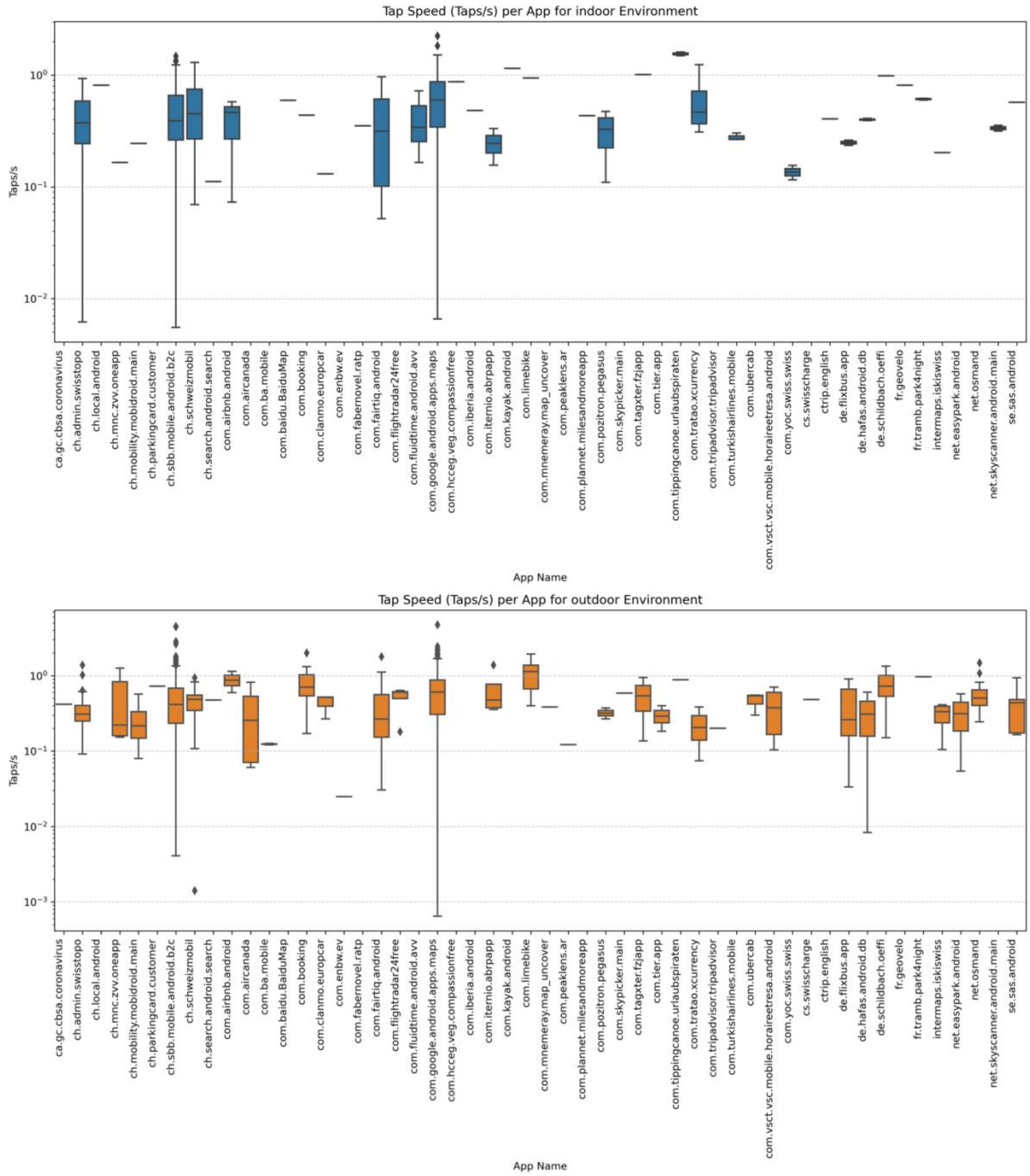


Figure 50. Boxplots of map app tap speed across 2 environmental groups

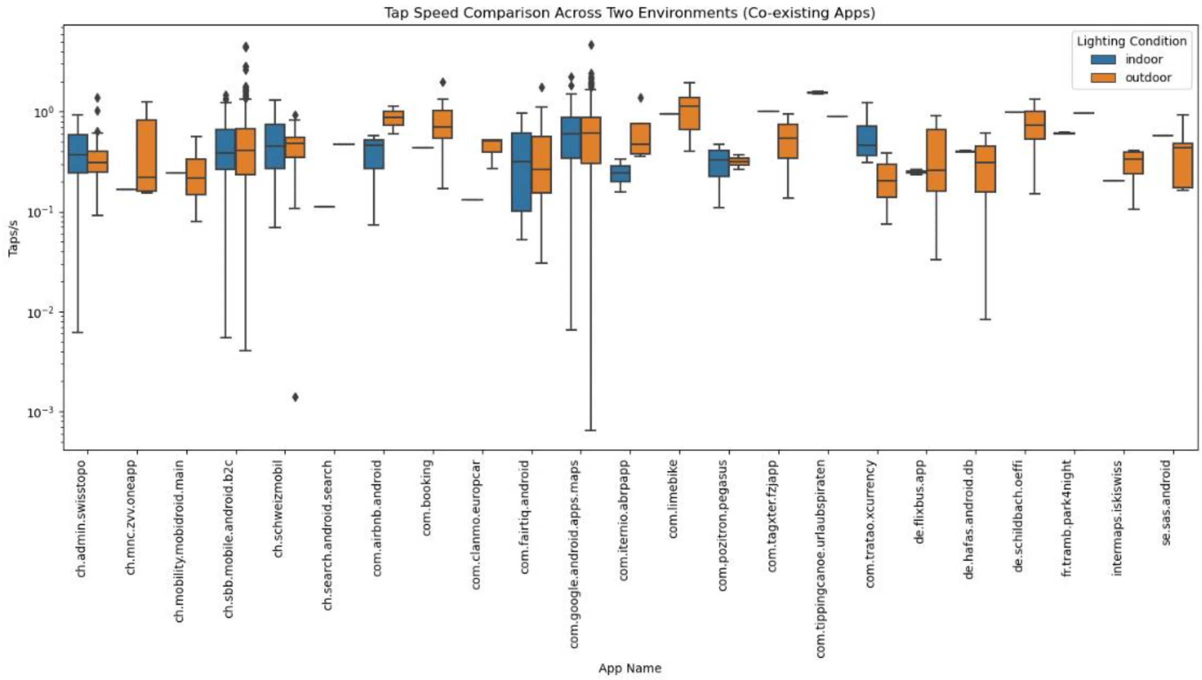


Figure 51. Boxplots of map app usage duration across 2 environmental groups (Only common apps)

5 Discussion

This section discusses the research questions, including the evaluation of the indoor and outdoor detection methods and the interpretation of the findings on the map app usage in different lighting conditions. Limitations of the project and suggestions for future work are also included.

5.1 Discussion of Research Question 1:

Recap Research Question 1:

- How can we leverage the taps, light, and GPS data to help distinguish between indoor and outdoor mobile map app usage?

By taking reference from former research related to indoor/ outdoor detection models involving ambient light (Dastagir et al., 2024; Radu et al., 2014; W. Wang et al., 2016; F. Zhu et al., 2024; Y. Zhu et al., 2019), I set up three models for environment detection: one using building footprint only, one using light only, and a lightweight joint model that combines building boundaries and ambient light. To evaluate the accuracy of the models, I manually labelled 530 reference points and compared the accuracy, precision, recall and F1 score across the three models. The accuracy and precision score of the joint-factor, lightweight method is highest while the performance of the light-only model is the worst. This result aligns with Xu et al. (2014), where they achieved 96% accuracy for indoor, 91% for outdoor, and 72% for semi-outdoor detection using a combined light intensity and GPS module method although the difference is that they used GPS modules while I used GPS coordinates along with building footprints downloaded from volunteered geographic data. The poor performance of the ambient light-only method also supports Xu et al.'s conclusion that ambient light alone is not sufficient to distinguish outdoor and semi-outdoor scenarios (Xu et al., 2014). This observation is further validated by MoT data. In some cases where light value skewed to very low or very high, the detection of model is likely to be wrong. For example, refer to Table 5, reference point 24764 is clearly outdoors in a park, but the ambient light recorded was very low, possibly because the phone was in a pocket or under shaded, was identified as indoors by the light-only model. Similarly, for reference point 12345 where participant was inside the Basel main train station, had a recorded light intensity of 20,693 lx was identified as outdoors by the light-only model. However, as shown in Figure 52, the building has a large window on the front side, so although the light intensity is high, by comparing the coordinate of the tap, the location is still indoor. On the other hand, reference point 36814 is a point under the transparent cover on the surface of Bern train station. Since there is underground area beneath the station, the building footprint-only method identified it as indoor. However, with light intensity of 6,164 lx, it is clearly an outdoor setting as indoor light levels are generally below 1,000 lx based on both literature and manual measurement as shown from Table 1-4. This sample shows that building footprint-only model also cannot provide high accuracy on its own.

Figure 52. Appearance of Basel train station (Source: SBB)

Since the reference points are manually assigned, they may not represent absolute ground truth data. However, comparing the results with the Low Light and Strong Light clusters might help validate the method. These clusters were identified using K-means clustering. As a quick recap, the Low Light group has a median of 205 lx and mean of 1,738 lx, while Strong Light has a median of 37,066 lx and mean of 45,374 lx and. Based on prior knowledge from Table 1 or through measurements value from Table 2 to 4, 205 lx is a typical indoor room, 1,738 lx might mean a well-lit indoor space with large windows, and over 37,000 lx clearly points to outdoor on a sunny day. By comparing the normalised tap count distribution in map app (Figure 26 and Figure 46), for example, SBB mobile which has 52.15% in Low Light and 87.80% in Strong Light in terms of light condition clustering (35.65% difference), while the distribution by the environmental states, derived from the joint detection method, is 51.8% indoors and 86.1% outdoors (34.3% difference). As for Google Maps (Figure 27 and 47), the distribution is 88.34% in Low Light and 79.63% in Strong Light (8.71% difference), as well as 90.0% indoors and 86.3% outdoors (3.7% difference). Consider that K-means is a machine leaning clustering algorithms, and the sample size vary between the Low Light/ Strong Light clusters and indoor/ outdoor groups is different, the small differences between the two methods suggest the lightweight joint model is reasonably effective and satisfactory.

However, although the lightweight method can be a proxy for indoor and outdoor detection, there are still potential issues with this method. Based on the workflow chart (Figure 7), out of the six scenarios, the model includes four possible outcomes for outdoor but only two for indoor. This might create bias toward predicting outdoor while underrepresenting indoor cases. The joint method has a very high precision score (0.91), however, the recall is lowest among the three models which indicating it is missing lot of indoor cases. On the other hand, the F1 score is highest on the building footprint-only method, which shows better balance between precision and recall compared to the joint model.

Moreover, as there is no ground truth collected in the data, the 530 reference points are allocated manually by evaluating the light intensity and comparing the aerial photos from Google Maps. First of all, a sample size of 530 points out of the 42,106 map points, accounts for 1.26%, is very small. It is time consuming and the efficiency is not high as I have to manually exclude many uncertain locations, for example, like those near the buildings, along the road, and some location which has both surface area and underground area, like the Irchel campus or ETH Polyterrasse.

On the other hand, the two factors used in the model, ambient light and building boundary information from OSM, has their own limitations. The technical limitation of ambient light is further discussed on the 5.3 Limitation sub-section. As for OSM, although it is a widely used collaborative mapping platform, there are several limitations in terms of accuracy and reliability. A key concern is that only around 25% of its contributors have professional GIS experience (Brovelli & Zamboni, 2018; Z. Wang & Niu, 2018), which often leads to inconsistent, incomplete, or imprecise data when compared to authoritative sources. The crowdsourced nature of OSM also results in wide variability in data quality across regions (Basiri et al., 2016; Cantarero Navarro et al., 2020), with no consistent method to assess how data was collected, making it difficult to generalize accuracy findings from one area to another (El-Ashmawy, 2016; Klipp et al., 2021). During my progress of downloading the building footprint from OSM, the number of buildings can vary over time, or over different laptops even using the same command or query to run the task. Not only because OSM is continuously update, but there are also changes in the underlying database in the tagging schemes and data structure in OSM, as well as the API limited the query area size. Though the difference is not large, but re-production in other laptop may have a slightly different result.

Nevertheless, it is important to emphasise that achieving high accuracy in indoor/ outdoor detection is not the primary objective of this thesis. Rather, the aim is to explore whether tap data, when combined with ambient light and GPS coordinate information, can serve as a proxy for understanding users' environmental context in a lightweight and straightforward manner. This approach seeks to infer contextual information without intruding on user behaviour or compromising privacy. The method presented here differs notably from traditional techniques, as the MoT collects tap and contextual data passively in the background and only when explicitly authorised by the user. In contrast, other studies on indoor outdoor detection often impose constraints on how participants interact with their devices, for instance, requiring them to hold smartphones in front of their chest while walking (Zhu et al., 2019), or to maintain a horizontal position at a specific height to ensure signal reception (Zhu et al., 2024). As a result, those experiments are typically limited in study duration (Wang et al., 2016) or confined to specific routes (Xu et al., 2014; Zhu et al., 2012; Ali et al., 2018).

Therefore, by comparing the reference points and the usage patterns across lighting conditions and environment states, the results suggest that the lightweight joint detection model can serve as a reasonable proxy for distinguishing between indoor and outdoor environments

5.2 Discussion of Research Question 2:

Recap Research Question 2:

- Can tappigraphy, combined with light sensor data, be used to understand how the variation of ambient light influences mobile map app usage?

General descriptive

According to our data which has already filtered out the session with at least one map app usage, the non-map app usage is still dominant (78.46%) than map app (21.54%). And among these data, the most used categories are Communication, Travel and Local, Social, Maps and navigation, Tools and Game. The most used apps in Maps and Navigation category are SBB mobile, Mapy and Swisstopo, while the most used app in Travel and Local category are Google Maps, Airbnb and Booking.com. In term of popularity, Google Map, SBB mobile, Booking.com, Flixbus, DB Train and Airbnb are used by at least 10% of the participants, with around 92% used Google Maps. This result is not surprising, consider Google Maps is the most popular map app; SBB is the main train system corporation in Switzerland; Mapy and Swisstopo provided offline map for hiking; Flixbus is the trans-Europe bus company; DB Train is the major train system in the neighborhood country, Germany; Booking.com and Airbnb are popular apps for accommodation booking.

From the general light intensity of all taps individual level, the median is 105.67 lx, which is a typical environment for an indoor household room. While the mean light is around 1,300 lx, referred to the bright indoors or dark overcast. The high difference between the median and mean indicating it is skewed by the high reading. On the session-wise data, from Figure 12, it is observed that the overall ambient light records are drawn to the lower end, it indicates that most of the phone sessions happened in a relatively dim environment which might infer an indoor setting.

From the heatmaps which show the weekly and hourly pattern of tap counts and map app duration, it is observed that in general, phone usage is more profound on Friday and weekend than Monday to Thursday. The active hours on weekend spans from morning (6am) till evening (8pm). While for weekdays, except for Friday, the active hour is most notable at 6-7AM and 4-5 PM. On Friday, similar notable usage can be found at 7AM, but it is also noting the usage is high at 11 AM and from 3-8 PM. The map app usage pattern is accords to the finding of Reichenbarcher et al. (2022) where map app usage dominant from Thursday to Sunday and peak at 1PM, 4-5PM and 7PM. The difference is that the heatmap data in my thesis is generated form the standardized tap counts while

Reichenbarcher et al. (2022) used map taps per hours. For the heatmap patterns of Google Maps, the usage patterns are similar, where participants use map app mainly from Friday to Sunday, and more active from 1 – 8 PM. This bimodal temporal peak across the day may because people commuting to and from work in the morning and evening. Moreover, the map app usage at evening is higher than that of morning.

Correlation Between Light Metrics and Map App Usage Variables

Regarding the general Spearman correlation matrix between ambient light metrics and map app usage variables, no significant correlations were found for most light-related variables, except for light range per session. The strong correlation between tap count and tap duration suggested that they are consistent indicator in map app usage. Nevertheless, the weak correlation between light metrics (except for light range) and map app usage variable is somewhat unexpected, as it was initially assumed that map app usage might increase under strong ambient light due to situational visual impairments such as screen glare. The insignificant result could be attributed to the limited amount of data with high light intensity readings, as the light data is highly skewed toward the lower end.

Nonetheless, the light range variable shows significant relationships with all map app usage metrics. Specifically, light range has a positive correlation with total tap count, map app tap count, total session duration, and map app session length. In contrast, it has a negative relationship with the proportion of map app tap count, map app duration, tap speed, and map app tap speed. In other words, when ambient light fluctuates, participants tend to tap on their phone more and have a longer general phone usage but spend relatively less time on the map app itself, and with slower interaction speeds.

This observation aligns with findings from Qiao and Wu (2023), who studied the impact of light and dark map modes across different lighting environments. Their research showed that performance was best when the map display mode matched the ambient light, i.e., light mode during the day and dark mode at night, suggesting that visual consistency improves usability and lowers cognitive load. Eye-tracking experiments indicated higher accuracy and fewer fixations when lighting and map mode were corresponded, supporting this statement. Similarly, Grimes and Valacich (2015) demonstrated that greater cognitive load tends to result in slower clicking speeds and longer task completion times in online tasks, which could explain the lower tap speed and longer session duration observed here under conditions of high light intensity variability. In terms of cognitive aspect, under strong light condition, human' s pupil' s contraction to regulate light can mask the subtle dilations caused by cognitive load while the constant need to adapt the changing light conditions requires additional cognitive resources (Meethal et al., 2024; Palinko & Kun, 2012).

Beyond cognitive explanations, a high light range during a session may also imply that users are transitioning between different lighting conditions, such as moving from indoors to outdoors, passing through shaded areas, walking under tree canopies, or even navigating while driving through tunnels. In such dynamic environments, screen visibility may be inconsistent, making it harder to maintain focus or interact efficiently with the map apps. This could contribute to the reduced proportion of map usage and slower tap speeds.

Map App Usage by Lighting Condition Clusters

To examine the variation of map app usage of different lighting conditions, I first use K-means unsupervised machine learning algorithm to cluster the session-wise data. The optimal number of K is two, thus, I classified the median light intensity of the session-wise data into Low Light and Strong Light cluster. The range of Low light cluster spans from 0.14 lx to 23,492 lx (IQR: 36 – 1,161.62 lx), and that of Strong Light cluster range from 23,789 lx to 96,670 lx (IQR: 37,066 - 53,117.17 lx). As mentioned in the discussion part of the research question 1, based on the descriptive of the two light clusters, it can be already say that Low Light cluster refers most of the indoor environment, while the Strong Light cluster refers the very bright light environment in outdoors.

General Map App usage across the lighting clusters

By comparing the tap counts across the cluster, there is significant difference in the total tap count and the map app count proportion, which shows that the total tap count is lower in Strong Light cluster but higher map app tap count proportion throughout the session.

In terms of session duration, the finding is similar tap counts, where the overall session length is shorter in Strong Light cluster while the map app duration proportion is higher there. Nevertheless, no significant difference is found in tap speed between the two clusters.

These findings show that the general usage of phone is lower in strong light condition than low light condition, but map app is more obvious in bright light condition. It infers those individuals spend more time on smartphone in lower light levels, which is typically in indoor environments, but use map app more in bright light condition, which often associated with outdoor setting. The lower light condition may provide a more comfortable condition for extended smartphone use. In contrast, bright light conditions in outdoor may happened with screen glare, situational visual impairments, or other distractions from the environment depends on the activity. The higher map use proportion indicated that people use map app more, probably in outdoors which reflects the need of outdoor navigation or travelling.

In-app User Behaviour across the lighting clusters

The in-app analysis reveals distinct behavioral patterns between the Low Light and Strong Light groups, offering insight into how environmental lighting may influence map app interaction.

In the Strong Light group, likely to be associated with outdoor settings, SBB Mobile overwhelmingly dominates the Maps and Navigation category, accounting for nearly 88% of all taps. This suggests that users in outdoors are highly focused on transit and real-time navigation, possibly while actively commuting or navigating stations. The presence of *Mobility.ch, ENBW Mobility, and Fairtiq*, apps geared toward transportation, further supports the idea that map use in bright conditions is tightly tied to mobility.

In contrast, the Low Light group, which likely reflects indoor or stationary use, shows a broader distribution of taps across apps. This hints at more exploratory or planning-related behavior, where users might be researching routes, looking up locations, or browsing travel options rather than actively navigating.

The exclusive presence of *PeakLens* in the Strong Light cluster is especially notable. As an augmented reality application for identifying mountains, its usage is inherently tied to outdoor activities, particularly in clear, daylight conditions. This highlights how environmental conditions (like daylight) not only support but *enable* certain app experiences, such as AR in outdoor landscapes. This supports the idea that users choose apps based on not just location or time, but the very nature of the environment around them.

The chi-square test results confirm that these observed differences are statistically significant, with particularly strong associations for *Google Maps, SBB Mobile, and Swisstopo*. These shifts suggest that user engagement with map services is not uniform but highly responsive to environmental context, likely reflecting the immediacy of navigational needs outdoors versus the planning or exploratory behaviors indoors.

Although the general session duration is shorter in Strong Light cluster, for some apps, like Swisstopo, Mobility.ch, and Fairtiq, it shows longer median durations, inferred users tend to spend slightly more time in apps when in the Strong Light group which might reflect more complex use cases outdoors, such as checking public transport routes or navigating outdoors. However, most of these differences were not statistically significant, suggesting that while there is a general trend, it is not strong enough to generalize broadly. But it is interesting to note that Google Maps and ENBW Mobility did show significantly longer session durations in the Strong Light group, this may indicate that user is more engaged with these apps for sustained navigation or location tracking.

However, when it comes to tap speed, there were no statistically significant differences between lighting groups, either in clusters level or in-app level. While some apps like Swisstopo showed slightly slower interaction in Strong Light, the variation was not enough to suggest a meaningful shift in user behavior. This implies that environmental light does not clearly affect how fast or slow people tap within apps.

Map App Usage by Time Of Day

Since time plays a crucial role in lighting conditions, in order to understand how ambient light impact map app usage temporally, the map app usage in four time groups: Morning, Afternoon, Evening, and Night, are further analyzed.

General Map App usage

The results indicate that overall tap activity peaks during the Morning and Evening periods, possibly reflecting typical commuting hours when users actively engage with their devices for navigation or transit information. While map app tap count follows a relatively stable trend from morning through evening, it notably drops during the Night, which may be attributed to decreased travel activity and reliance on familiar or routine routes that reduce the need for map-based support. The proportion of map-related taps relative to total device usage is highest in the Afternoon and Night. This suggests that while overall phone interaction may decline later in the day, users who do engage with their phones at these times are more focused on navigational tasks, perhaps related to non-commute trips like leisure or long-distance travel requiring directional assistance.

A similar pattern emerges in session duration, where general usage is again higher during Morning and Evening, consistent with peak daily activity cycles. The map app session durations are relatively stable, but their proportion increases in the Afternoon and Night, reinforcing the idea that map apps become more purpose-driven tools later in the day, possibly used for specific tasks rather than background exploration.

In terms of tap speed, general tap speed is significantly faster during daytime, which may reflect hurried usage during transit or work hours. The slower tap speed at Night could suggest more deliberate interaction, potentially linked to more relaxed pace in non-working hour. However, no significant difference is found in map app tap speed among the groups, suggest, which means users engage with map apps in a relatively consistent manner regardless of time.

<u>In-app User Behaviour</u>

Most apps show higher usage during the daytime, particularly in the Morning and Afternoon. Apps such as Swisstopo, SBB Mobile, Booking.com, and DB Train exhibit this trend, aligning with typical commuting and travel planning behaviors during working hours. Some apps, such as ZVV, Mapy, Mobility.ch, and Trenitalia, appear to be used exclusively during the day, indicating their likely role in routine navigation, public transit, or mobility services that are less relevant in the evening or night.

In contrast, a smaller set of apps, including Uber, MyCicero, and Skyscanner, see greater activity in the Evening and Night, likely reflecting on-demand transport, leisure travel, or last-minute itinerary planning. Notably, apps such as TripAdvisor, Airbnb, and Geovelo are used almost exclusively at night, possibly due to late-stage accommodation booking or exploratory activities.

The statistically significant test from Chi-square test confirmed that usage frequency across time groups was significantly associated for key apps like SBB Mobile, Google Maps, Swisstopo, Booking.com, DB Train, and Air Canada ($p < 0.001$), reinforcing that time of day plays a meaningful role in shaping app engagement. While session duration remained relatively stable across the day for many apps, notable exceptions exist. For instance, Swisstopo and Air Canada had shorter sessions at night, which may indicate quicker lookups or limited interaction needs during off-hours. Conversely, Booking.com and Fairtiq showed longer nighttime sessions, perhaps reflecting more deliberate or complex user tasks, such as comparing lodging options or checking travel validity late in the day. Statistical testing revealed significant differences in session duration for Google Maps, SBB Mobile, Booking.com, Swisstopo, and DB Train, suggesting these apps are more sensitive to temporal context.

In terms of tap speed difference, only Google Maps and DB Train showed statistically significant differences in tap speed across time groups, with Google Maps has a slower tap speed at night, and DB train has a slower tap speed in the evening. This suggests that while temporal fluctuations exist, tap speed may be less consistent as an indicator of time-based usage shifts for many apps, or that app design standardizes user interaction regardless of context. The slower tap speed may serve as a proxy of reduced cognitive load or user engagement intensity. Although slower tap speed associated with reduced cognitive load may seems contradictory to (Grimes & Valacich, 2015) finding, but cognitive load is a complex measure that one cannot have an absolute statement about whether slower or faster tap speed infer to heavy cognitive load which it may varies depends on the task (Meethal et al., 2024) . Therefore, I believe that in general phone usage, especially for the slower tap speed at night, may still infer the reduced cognitive load without the urgency of app usage.

Map App Usage by Environmental States

The map points in Switzerland were further classified into indoor and outdoor groups via the lightweight joint algorithm that considers both building footprints and ambient light level, to allow a more accurate analysis of map app usage in indoor versus outdoor environments. It is important to note that K-means clustering method, which classified the Low Light and Strong Light groups, may already suggest indoor and outdoor settings, it remains an unsupervised machine learning method. The Low Light cluster, for instance, spans a wide range of illuminance values up to 23,492 lux, which covered the spectrum of light intensities typically found in outdoor settings. As discussed in section 5.1, ambient light alone is insufficient for precise indoor - outdoor detection, since a single map point with high light intensity does not necessarily indicate an outdoor location. In some cases, users may place their phones near window or located under a transparent roof. By incorporating building footprint data, the lightweight algorithm provides a more reliable classification of whether a user is physically indoors or outdoors. The following sections will further discuss map app usage patterns both in general and at the individual app level.

General Map App usage

By comparing tap counts across indoor and outdoor environments, a significant difference was observed in total tap count, with indoor sessions recording more taps overall. This suggests that users tend to engage more frequently with their phones when indoors, potentially due to having fewer movement-related constraints (e.g., walking or navigating), allowing for more focused and extended interaction.

Regarding session duration, the data showed that general phone usage sessions are significantly longer indoors, likely reflecting users' ability to concentrate on their devices in a stable environment. On the other hand, map app usage represents a greater share of phone session time in outdoor settings, suggesting that outdoor sessions are more focused around navigation tasks, where the map app is often the central or sole application being used.

Finally, likewise in the Low Light and Strong Light clusters, no significant difference was found in tap speed (taps per second) between indoor and outdoor groups. This implies that the speed of interaction with both general phone apps and map apps is relatively unaffected by environmental context, potentially due to users' adaptation to different lighting and movement conditions, or because tap speed is influenced more by personal habits than external factors.

<u>In-app User Behaviour</u>

The analysis of in-app behaviour across indoor and outdoor settings revealed nuanced differences in how map applications are used depending on environmental context. While many apps were commonly used in both settings, distinct patterns of exclusivity, dominance, and usage intensity emerged, reflecting differing user needs and situational demands.

Several map apps were found to be exclusively or predominantly used in either indoor or outdoor contexts such as OpenStreetMap, Uber, Tier, and EasyPark are likely aligned with real-time outdoor activities like navigation, scooter renting, or parking. These apps inherently support tasks that are spatial and mobility-focused, which naturally occur in outdoor environments. Conversely, indoor-exclusive apps like Baidu Map, RATP, and Fluidtime may serve functions more suited to planning, itinerary management, or localized public transport services, often explored during idle time indoors.

Some widely used apps displayed strong environmental preferences. For example, SBB Mobile and Switzerland Mobility were significantly more tapped in outdoor environments, likely due to their utility in real-time public transport tracking and route finding. Google Maps, although dominant in both environments, was even more frequently used indoors. This could indicate its role in pre-navigation planning or indoor browsing, such as checking locations or viewing area information. Interestingly, Swisstopo, a topographic mapping tool, had much higher indoor usage, possibly reflecting its use for terrain analysis or trip planning before heading outdoors.

App usage duration varied significantly for nearly half of the apps analyzed. Notably, apps like SBB

Mobile, Flixbus, and Booking.com showed longer sessions in outdoor settings, which may reflect prolonged engagement with tasks like route tracking or booking during travel. On the other hand, apps like ZVV and Iskiswiss had longer sessions indoors, possibly due to users dedicating time to schedule checks or planning while stationary. These differences underline how environmental context shapes the depth and type of engagement with specific app features.

It is to note that tap speed usually shows a less significant difference compare to tap counts and phone session duration. It may indicate that tap speed in general is in a constant rate disregard the temporal and spatial variation.

Suggestion for Map app design regarding ambient light variation

Since the results show that the higher fluctuation tends to hinder map app usage, reflected by lower map app tap counts proportion, lower map app session duration proportion, slower general tap speed and slower map app tap speed, and given that the ultimate goal of studying user context is to support more user-friendly, user-centred app design that enhances user adaptivity, there are several design suggestions on map app design for addressing ambient light variation.

First of all, the built-in auto-brightness functionality could be improved to respond more quickly to the dynamic light conditions (Tigwell et al., 2018). However, research stressed that relying on auto-brightness function alone is not sufficient to address the visual discomfort on screen (Tigwell et al., 2018; Yu et al., 2015). Additional measures could include implementing smart color scheme transformations under different light conditions that maintain readability while preserving the app’s design intent, as well as exploring the use of High Dynamic Range (HDR) displays to enable context-specific interface color modes. Prior research by Yu et al. (2015) proposed *ColorVert*, a system that adapts color schemes in mobile web browsers based on ambient light using Derrington-Krauskopf-Lennie (DKL) color space for effective transformation, which could also be applied to map apps. Similarly, Qiao and Wu (2023) suggest that when both light and dark modes are available, users should be encouraged to switch modes based on their current lighting environment.

5.3 Limitation

While MoT can respect participant's privacy at a very high level, there are several limitations of the project.

Technical Limitation

One of the limitations of this project is the accuracy of the illuminance measurements. According to the National Optical Astronomy Observatory, the maximum sunlight reaches up to 107,527 lux (NOAO, 2015). Other standards, such as Schlyter (2023), report up to 130,000 lux under direct angle of sunlight. However, the raw data of MOT contains records which up to 359,845 lux, which is unreasonably high for ambient light. Ambient light is recorded by from the light sensor near the front camera of the mobile phone. I assume that different phone models and brands may have different camera qualities, resulting in discrepancies in light measurement.

Some former studies have explored accuracy of light sensors in smartphones and tablets associated with different applications for measuring illuminance, with and without diffuser dome attached to the devices (Godinho Vaz et al., 2021; Cerqueira et al., 2018). By comparing reading with traditional lux meters, these studies found that the relative difference for measurement without a diffuser could range from 3% to 392% under LED light source and that could even rise up to over two thousands percent under Xenon arc lamp environment (a highly specialized gas discharge lamp) (Godinho Vaz et al., 2021). Furthermore, they showed that different mobile operating systems and brands have varying light sensor. For example, Motorola smartphones performed satisfactorily even without light diffusers in specific scenarios, while Nokia phones did not perform well in any forms of experiment settings (Godinho Vaz et al., 2021). These findings might infer that the build-in light sensor in mobile phones may not be as accurate for light measurement as standard lux meter.

Even some light meter applications available on the Play Store and Apple Store recommend attaching a light diffuser for accurate measurements. For users without professional equipment, it is suggested to attach a piece of standard white printer paper (80 g/m² or 22lb) in front of the camera to serve as a paper diffuser (Lightray Innovation Gmbh, 2025). In order to test the difference of the light measurement with and without the diffuser, I took measurement in two spots around Irchel (Table 10). Without the diffuser, the difference range from -75% to 55%, which is a fluctuate reading. A reminder '*Diffuser Missing: Your light meter needs a diffuser*' was also prompted in the absence of that. During the data collection period of MOT, participants were asked to use mobile phone as usual, without any additional diffusers, there may be discrepancies in the accuracy of ambient light recording.

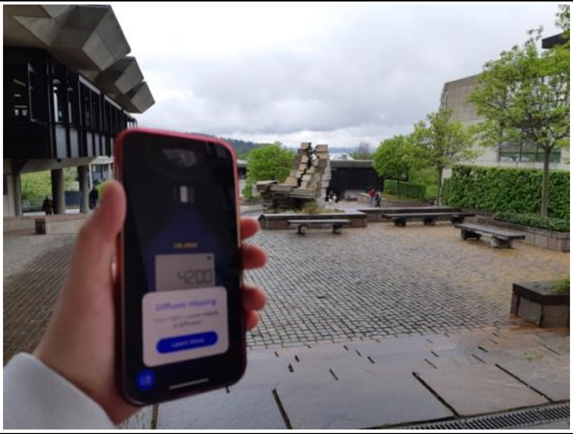
Without Paper Diffuser:	With Paper Diffuser:
	
Reading: 4200 lx	Reading: 2400 lx
	
Reading: 1000 lx	Reading: 2200 lx

Table 10. Ambient light measurement with and without diffuser

Project Limitation

In terms of tappigraphy in general, the data is large and noisy. It records every single taps of users over the study period. Based on different purposes or activities, the number of taps can vary a lot. For example, apps in Game and Communication categories may involve many more taps than apps other categories because of the game design and text typing. In my project, more than 5 million taps were recorded from 60 participants who used their smartphones over a period of two weeks. Many records showed ambient light readings of less than 5 lx even during daytime. Apart from the technical limitation related to diffuser as mentioned above, this could indicate the mistaps or unintentional taps occurred inside bags or pockets when participants did not lock the smartphone properly, or vice versa, due to the accidental unlock from Face ID. As I focus on map app usage, which only involves *Maps and Navigation* and *Travel and Local* categories as a small part of the total tap counts, detailed data cleaning steps needed and only a small portion of the data was useful for further analysis. Besides, smartphone behaviour can also vary a lot between individuals, and even for the same person over time (Corbyn, 2021). A sudden drop in smartphone-based communication could be either a sign of social detox, or it might simply mean someone is communicating in person instead (Corbyn, 2021). As for map app usage, if a participant has more taps on maps, it could indicate that they are engaged in a long session of map use, or they are simply entering a long place name. The similar difficulty was reported in mobile app usage analysis by Li et el.(2022) where they could not determine whether users of long session travel apps were actually traveling or only planning to a journey. Another factor to consider is the swipe typing function available on Android, which allows participants to type on the Swype keyboard without lifting up the fingers, enabling them to type smoothly and with fewer taps issued compared to traditional keyboards. This small habit could lead to differences in tap counts among participants. In other cases, some individuals might prefer using a build-in navigation system in private car rather than relying on the little screen on their smartphone while driving. While tap count can act as a proxy for map app usage, various technical, behavioural, and contextual factors make it challenging to interpret precisely.

Moreover, there may be bias in the participants group. Although the project welcomed participants aged 18 and 85 for participation, the outreach of university may have caused the age distribution to lean towards a younger group. It is noteworthy that older adults may lack the technological skills required to use smartphones or mobile map apps. The ability to comprehend English was also one of the criteria for participation in the MoT. As a result, older locals may have been more likely to be excluded from the participant pool. Additionally, MoT is only available on Android operating system, and users who are accustomed to using a stylus pen were excluded. This introduces a bias in favour of a relatively younger, more tech-savvy group. This bias in participant pool align with the findings of Corbyn (2021) who notes that research often draws from predominantly white, wealthier, and more highly educated populations.

In terms of the data limitations of MoT, as discussed in the Data & Method section, the unit of time presents an issue. The timestamp of taps are recorded in milliseconds while the phone unlock and lock times are recorded in seconds (1 second equal to 1000 millisecond). This discrepancy complicates the calculation of phone session duration, which is one of the metrics on map app usage, and therefore also affects the calculation of tap speed (number of taps per second), leading to some data loss. Furthermore, the local timezone did not update automatically as participants travelled. As a result, our data analysis was limited to considering only those who stayed in neighbouring countries to Zurich, such as Germany, Italy and France, leading to data loss during cleaning and some inconsistent sessions.

Another limitation of this study is that the analysis was conducted at session-wise level for the three classification methods, with data aggregated from tap level to session level. In this approach, classifications such as Low Light vs. Strong Light, Morning/ Afternoon/ Evening/ Night, and Indoor vs. Outdoor, are determined by the mode of the number of taps within a session. However, this method risks losing more fine-grained information. For example, if a participant used the smartphone with 30 taps outdoors and 29 taps indoors, the session would still be classified as outdoor usage. Similarly, if a participant unlocked their smartphone at 11:57 PM and locked it at 12:04 AM (assuming a roughly even tap distribution), the entire session would be classified as a night session, even though a substantial portion occurred during the evening. These cases illustrate how the aggregation method could compromise the accuracy of the environmental state classification.

In addition, there are many external factors that are likely to influence map app usage, such as spatial familiarity, presence of companions, individual sense of direction, and spatial anxiety (Nivala et al., 2007), which were not captured in the MoT project dataset. Of these, familiarity with the environment arguably plays a particularly crucial role in determining whether or not individuals rely on map applications. Unfortunately, in the MoT dataset, no indicators of spatial familiarity were available. Although previous research, such as Zingaro (2022) and Zingaro (2024), has explored the relationship between distance from home and map app usage, as well as the effects of spatial anxiety and sense of direction on map app usage, it is important to note that neither distance from home nor sense of direction necessarily equate to familiarity with the environment. One could be very familiar with a location far from home (e.g., workplace, family town) or unfamiliar with a nearby area (e.g., a newly developed neighbourhood). The absence of such contextual variables limits the depth of interpretation in this study.

5.4 Future Work

MoT provides valuable insights about user interaction in different real-world contexts with very few privacy concerns compared to traditional laboratory settings. Map app usage metrics such as tap counts, session duration and tap speed can be derived from the tap data. However, enriched interaction patterns maybe missed, such as panning, zooming, pinching such kind of gesture interaction, or how exactly participants use the map app in different state panels, such as search, direction or just exploration mode in various contexts. There is a tool named MapRecorder which is an innovative "wrapper" application designed to study how people interact with mobile map app, particularly Google Maps (Savino et al., 2021). The application's data collection capabilities are extensive and multifaceted. Similar to Mot, it records the unique session identifier as well as other session details. On top of that, it records in-depth user interactions, including the compass orientation, precise touch-point coordinates on screen, gesture interactions (like pinch, tap, zooming, panning), keyboard input, and map interactions (with changes in zoom levels and centre points). In addition, MapRecorder organizes user interactions into four main states for analysis, including: Search (when users type queries), Place (interaction with specific locations), Directions (route lookup from the starting point), and Map-View Manipulation (panning, zooming, or viewing the map) (Savino et al., 2021). This state-based tracking makes MapRecorder a powerful tools that enables researchers to identify specific usage patterns. Future research on map app usage could benefit from tools similar to MapRecorder, allowing for more comprehensive analysis of user interaction patterns beyond basic tap data.

This thesis examined the general influence of light on map app usage. Lighting condition was classified into Low Light and Strong Light by K-means clustering as a simple and direct algorithm. In the future, more in-depth studies on light features could be considered, such as incorporating colour temperature to differentiate between warm and cool lighting environments, or distinguishing between artificial and natural light sources. Additionally, better handling of nighttime conditions, where light levels are low but environmental context differs, could further refine the classification.

Previous research has shown that lighting design with different colour temperatures can have significant effects on social behaviours across various socio-spatial contexts (Casciani, 2020). For example, warm white light has been found to foster more positive social interactions, encouraging politeness and promoting friendliness among people, whereas cold white light tends to enhance concentration and task-oriented behaviours, though perceptions can vary by gender (Casciani, 2020). Similarly, the research of Song and Yamada (2019) suggested that green and low-intensity light animations made users perceive a computer as more positive and friendly, while red and high-intensity animations were perceived as negative and hostile. According to Lanz’s (2021) master’s thesis, the use of blue accent lighting was associated with a greater calming effect compared to white lighting, as measured by emotional response tracking via the iMotions facial recognition software and self-assessments. Furthermore, Shishegar et al. (2021) found that light with higher colour temperatures (bluish) promote alertness and wakefulness during daytime hours and can suppress melatonin production, whereas light with lower colour temperatures (yellowish) are more suitable for evening hours as they are less likely to disrupt sleep patterns.

From these examples, it is evident that even when light intensity stays constant, variations in colour temperature can make significant influence on human perception and affect people both emotionally and physically. It is therefore suggested that future work should consider testing the effects of different lighting temperatures, especially at night, to explore whether they impact map app usage or user behaviour more profoundly.

6 Conclusion

This study provides an insightful analysis of mobile map application usage under varying lighting conditions, both spatially and temporally, by utilizing tappigraphy data, GPS coordinates, and ambient light information from smartphone sensors. Tappigraphy, a minimalist data collection method originating from neuroscience, unobtrusively records touchscreen interactions while preserving a high level of user privacy. Understanding the context of mobile map app usage is essential, as it can offer valuable insights for enhancing the adaptability and user-centered design of map-based services.

This thesis also proposed a lightweight, privacy-conscious approach for indoor-outdoor environment detection. By comparing GPS coordinates with building footprint data from VGI platforms and incorporating ambient light readings, the method offers a simple yet effective proxy for determining environmental context. Compared to existing indoor-outdoor detection models which often require extensive sensor input or structured experimental setups, this joint detection approach is computationally efficient, requires fewer data inputs, and still yields satisfactory results. Although exact accuracy could not be verified due to the absence of ground truth data, evaluation through reference points and clustering analysis indicates that the model performs reasonably and can serve as a proxy for distinguishing environmental states.

Despite its limitations, this study contributes to the Human-Computer Interaction (HCI) field by enriching the understanding of mobile map app behaviour under different contextual conditions. Results suggest that ambient light variation is positively associated with general phone usage, while high light fluctuation may lead to reduced map app engagement and slower interaction speeds, probably due to visual impairment or environmental restrictions. These findings reflect the nuanced ways environmental factors shape user behaviour.

Future research could explore more fine-grained data collection or integrate additional environmental indicators such as lighting temperature, or other refined lighting conditions. Extending this work could provide further insights into how environmental context influences mobile navigation and help inform more adaptive, responsive app design.

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Declaration

I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis. AI applications, including ChatGPT-4, Claude 3.7, Elicit, and Scite were used to improve the readability and clarity of the writing, as well as to support literature exploration.

Eunice

Choi Yeung Lo, 30.04.2025