Smartphone pervasiveness: exploring social interaction using behavioral and self-reported smartphone data

Report for Social Dynamics Lab (2024, February)

Davide Vandelli

Summary index

Introduction, research question and theoretical framework

The ubiquity of smartphones transcends many social boundaries. Over the course of many human societies, small devices have progressively become more accessible, from the rare chunky Motorola mobile phone in 1973 (U.S. Patent and Trademark Office, 1975) to the ubiquitous flat smartphone. For Italians, one of the strongest predictors of advanced smartphone use is age and education (Fortunati & Taipale, 2014).

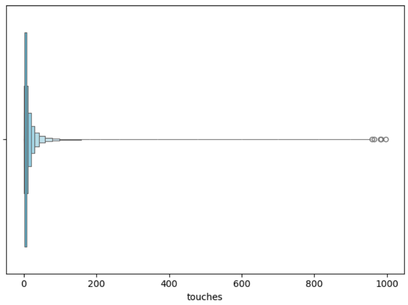
This report delves into situational social dimensions of smartphone usage, examining its presence in daily life from a sample of users. The purpose of this paper is to explore the main social attributes and time-patterns that describe the use of the smartphone for 145 university students in Trento, by combining sensor data and self-reported social context across several weeks. The theoretical reference belongs to a field of human and social behavior which is not yet fully established, but is found in examples such as Thulin et al. 's work (2020), which greatly inspired this report.

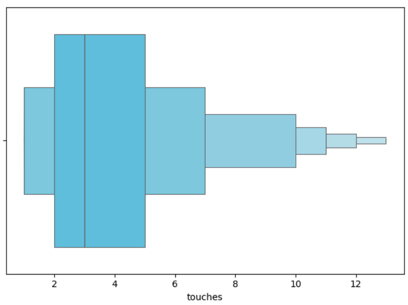
Existing research indicates that in younger individuals the smartphone affects communication patterns between peers, lowering thresholds regarding time and space; in other words, a more flexible social lifestyle enters their routines (Thulin et al., 2007). Similarly to many other widespread technological changes in human lives, no single phenomenon is in itself inherently damaging or benefitting to the individuals affected but compromising a mix of the two, which is the reason some research focuses of negative effects and ties phenomena like phone addiction to anxiety and depression in several Asian countries (Boumosleh et al., 2017) or feeling less connected when conversing with other people while smartphones are present (Misra et al., 2016; Humphreys et al., 2021), and other research deepens, for example, the use of smartphones for educational benefits and intellectual autonomy, by far positively exceeding the expectations in the world of e-learning (Morphitou, 2014).

The literature belonging to social research approaches the smartphone's effects with different methodologies and questions that advance our understanding on the phenomena involved, but less often data from the sensors embedded in smartphones is used. The scope of this paper is to utilize the touchscreen sensor as an indicator of phone usage during times in which the user is socially engaged with somebody, or in a social setting. The approach used is to simplify the highly dimensional data to a significant amount of features that can be interpreted and use them altogether with time.

WeNet Data and materials for pre-processing

In terms of materials, several libraries from Python and R programming languages were vital to this report; the former was used for cleaning and visualization and the latter for optimized statistical analysis.[1] All of the data derives from the WeNet project[2], which I was given the opportunity to perform analyses on their datasets. The specific data that was used in this paper comprises information regarding social and demographic description of the users and their smartphone touchscreen sensor collected in November 2020. To obtain more quality in the results, users who did not submit their data consistently or did not submit *touchscreen sensor* data were dropped out, from a sample of originally 241 users to 145. Afterwards, to avoid unusual spikes in activity from the *touchscreen sensor* (which are due to hardware malfunctions) have been replaced with the median; we may observe the impact of this change in the distribution in the boxenplot figure on the right of this paragraph.





Boxen plot distribution of touchscreen touches. Before (top) and after (bottom).

Furthermore, the *time diary* data comes with a 30 minute time frame unit per observation, meaning each time a user indicated what they were doing (and where, with who, etc.) it included the

[1] For more details on how the data was approached, refer to the report's Github's repository.
[2] WeNet

main activity they did for the 30 minutes in which a notification questionnaire was submitted to their phones, for the whole time of the experiment; *touchscreen sensor* data comes with an accuracy of a millisecond or less, so it had to be grouped by half-hours to fit the time frame of time diary.

Methodology and feature selection to predict smartphone usage and clustering categories of users.

The most theoretically relevant features are the touchscreen frequency and the factors that make up the social situation. The latter set is simplified by the feature representing the social company a user is with (friends, colleagues, relatives, partner, etc.), and though this model may be an oversimplification, the results are to be interpreted as exploration of a relatively new field of study. Other features were also used to build several models, including some that may describe more of an identity of the user rather than a situation the user is engaged in, but these serve the purpose of quantifying any possible influence on the identity of the user on the situational behavior. These features include the academic department of the user, their sex, and their cohort. They are used here as a representation of specific dimensions of the user's identity, as each of those features are arguably defining a big part of the student's social identity. It is here assumed that a student's social identity is mostly constructed with their academic identity (Smyth *et al.*, 2013), gender roles, and possessing generational differences from younger or older individuals - because other data on their identity is not available[3], and these three dimensions are respectively represented in the data by the academic department, the sex and the cohort.

The literature found on the phenomenon in which social interaction would be affected by how much a person would use their smartphone (or vice versa, the smartphone would affect the social interaction), foudn that gender did not associate with smartphone addiction in a significant way (Boumosleh et al., 2017). The user's age may be a predictor (Darcin et al. 2016), so the cohort was expected to play a bigger role.

Ultimately, the first model comprises the **sex**[4], the academic **department**, **cohort**, the **activity**, and obviously **whom** the user is with. The last two features are categorical, but both are tied to **time** which will be later incorporated in the analysis.

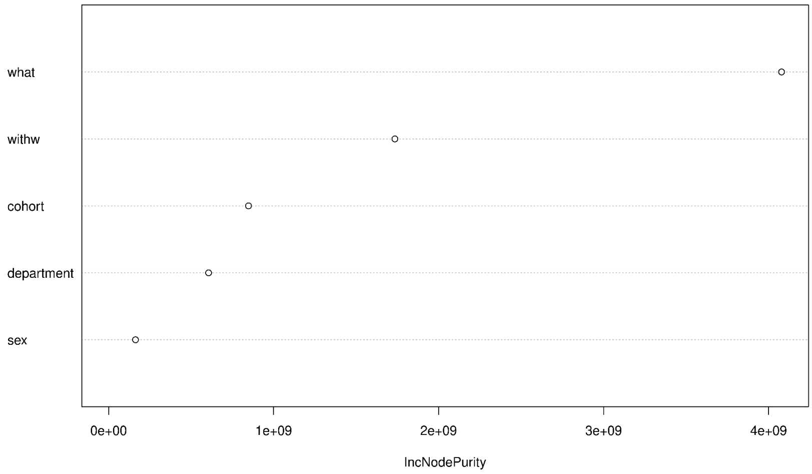
Since this first model possesses mainly categorical variables that are used to predict a continuous one - the frequency of usage of the smartphone - a **random forest** for regression with 500 trees was fitted onto the whole data. The goal for this random forest is not only to successfully predict new

[3] Other common social identity features are either impossible to obtain from the data or are not variant enough to bother, such as: economic class of origin; regional belonging; cultural diversity in their household, etc.

[4] Even though it is expected to not play a great role in phone usage, it is included. In the data this attribute is referred to as a binary variable, using "female/male" modalities, so it may not be treated as exactly equivalent to gender.

observations, but to better understand the interaction of the data between categorical variables[5]. Thanks to Random Forest's properties, the results are produced by splitting the target variable data with decorrelated trees, which is a very robust data exploration technique. In (1), the main features' importances are shown, and they are ordered by the increase in **node purity** of the regression trees, based on splitting the data by said predictors.

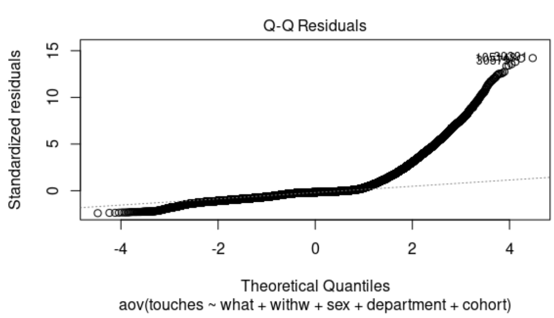
Figure 1. Node purity, random forest.



Node purity is a measure for trees that indicate how little variance there is in the splits of the continuous target variable, where each split comes from a categorical predictor. In a tuned model with 250 trees, the purity is very similar to the first, untuned random forest. From the tuning process, we know that the optimal parameter for the number of random variables candidate for splitting is 3.

Onto a deeper understanding of the features's effect, **ANOVA** (analysis of variance) is implemented in this report to compare the different effects of the categorical variables towards touchscreen frequency. The variables must be independent of each other and have the same variance. After visually checking the validity of predicted effects using Q-Q residuals plots and other metrics (Residuals vs Fitted, Scale-Location, Residuals vs Leverage), the assumption of having the same variance is deemed to be violated and the results should not be considered representative for almost half of the datapoints.

	Sum Sq (*log*)	F value	Pr(>F)
what	22.85826	549.41	smaller than $2\text{x}10^{-16}$
withw	19.38766	100.08	smaller than $2\text{x}10^{-16}$
sex	17.49004	105.03	smaller than $2\text{x}10^{-16}$
department	18.63982	47.36	smaller than $2\text{x}10^{-16}$



5 A pruned tree made as preliminary modeling of the random forest used all of the following attributes, in order of importance: the company, cohort, the activity, then department, and sex. So far, all were used in building the pruned tree, but its MSE is above thousands (356,455.3). This metric did not get reduced by far when using a Random Forest, which with different parameters, it is around 310,000.

cohort	24.62766	90.49	smaller than $2x10^{-16}$

The results are statistically significant, and are compatible with the Random Forest's importance plot in (1), as shown in the table below the Q-Q residuals plot, but the residuals are worryingly exceeding, and it is likely an artifact of the method.

Fig. 2. Kruskal-Wallis test

Variable	P value	Kruskal-Wallis X^2
withw	2.522445e-45	226.67634
what	3.945250e-120	668.52624
sex	4.995387e-04	12.11739
cohort	4.224835e-123	598.57984
department	2.371748e-80	390.68380

Due to failure to hold the assumptions in a trustworthy ANOVA, we may pass onto another model for evaluating the effect of categorical variables that has less assumptions: the **Kruskal-Wallis test**. The latter model divides the data into several groups based on their attributes - by variable - and compares them in terms of a quantitative variable. In this report I use Chi Squared; since it is a nonparametric test only the normality assumption needs to be fulfilled (Ostertagovà et al., 2014). From this model on to the end of the report I consider only the events in which the participant was with somebody, as more fitting to the research question as I'm headed towards less exploration and more interpretation.

After the KW test, the variables are usually tested using several techniques to understand better how significant the categories are; in this instance, the Dunn test was performed. The results are respectively in (2) and (3).

Fig. 3. Dunn test

Variable	Comparison	P value	Dunn test
withw	*Partner* Vs *Relative(s)*	***	-13.961
what	*Did not do anything special* Vs *Games*	***	11.345
sex	*Female* Vs *Male*	***	-3.481
cohort	*17-18* Vs *20*	***	19.108
department	*Humanities* Vs *Natural Sciences*	***	-15.271

The **Dunn test** compares each variable's category against each other, using the quantitative variable. Dunn's test then provides a statistic to evaluate how important the comparison is and how relevant it is to the data's structure.

For the sake of being brief about the results, only the strongest and most significant comparisons by Dunn test statistic are shown in (3), because there is a total of $(n\,x\,[n-1])/2$ results for each variable, where n is the number of categories in each variable.

Once again, the company and the activity categories are relevant, but a new importance is attributed to the **cohort**, surpassing the company's importance, only second to the activity. Another pertinent information regarding the cohort is that in the Dunn test the 5 strongest categories comparison were all between 17-18 year olds and all the other cohorts. This is an interesting finding, because it represents that the most significant differences can be found between the times in which the user was not alone and was 17-18 compared to users of any other age, possibly indicating a generational gap.

Before incorporating time into this analysis, one last method was implemented: **K-modes**. The purpose of this choice is to obtain typical profiles, modes of behavior that appear frequently throughout the time diary data. K-Modes is a sibling to K-Means, with the main difference that it is used on categorical attributes rather than continuous ones. In *figure 4* the most common associations of modalities for location, activity, and company is shown, altogether with some personal attributes.

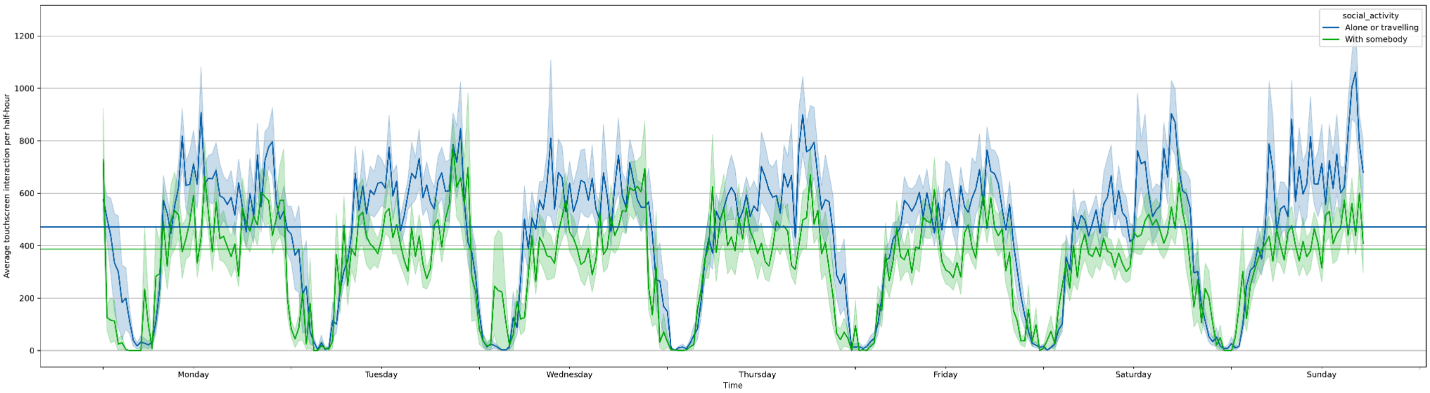
Fig. 4. K-modes clusters of context ***in social settings****.*

Sex	Cohort	Department	Where	What	Withw
Female	20	Natural Sciences	House (friends' others)	Study / work group	Partner
Female	21	Social Sciences	Home apartment/ room	Eating	Partner
Female	21	Law	Relatives home	Eating	Relative(s)
Female	24	Social Sciences	Home apartment/ room	Watching TV, video, YouTube, etc	Relative(s)
Female	19	Social Sciences	Relatives home	Social Life	Relative(s)
Male	20	Engineering and applied sciences	Home apartment/ room	Eating	Partner
Male	25-26	Engineering and applied sciences	Home apartment/ room	Sleeping	Relative(s)
Male	23	Engineering and applied sciences	Home apartment/ room	Social Life	Friend(s)

Note: this displays only the first 8 most important clusters from contexts of social behavior, e.g. excluding "Alone" or "No information" or "Expired".

Ultimately, these results from the previous exploration and evaluation of the features are used to simplify smartphone usage to incorporate time. A linear regression would retrieve promising results, but prior to any modeling between time and touchscreen usage a visualization of the relationship between the two is done in(5), as often it could be non-linear. Often, time-specific data analyses look for rhythms that are associated with polynomial, or sinusoidal waves patterns.

*Fig. 5. **Lineplot**. Week-Daily average touchscreen usage per half-hour:*



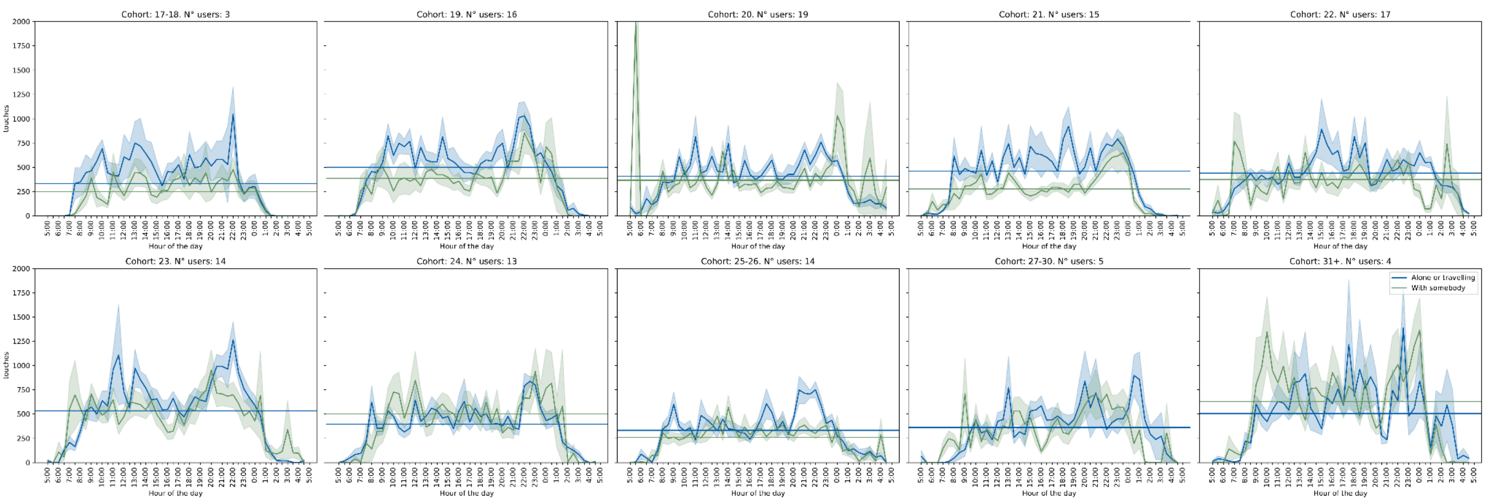
***users with somebody** vs **users alone** (resp. 50,967 and 28,812 observations)*

As the first visualization, a simple comparison in *figure 5* between users who were interacting with friends, relatives, classmates, colleagues Vs by themselves. It is assumed that when traveling *they likely were* in a social context, but *not actively interacting* with anyone; from now on, this difference is implied. For every plot, each group in the comparison will have a line of mean touchscreen frequency shown along the time axis, for an immediate comparison.

The main difference between users who are interacting in a human social context and those who are not is a lesser interaction with the phone: it is not a gigantic difference, but their confidence intervals at 99% do not overlap[6]. From *figure 5*, there are slightly more touchscreen interactions at night when a user is interacting with others, while when alone it seems they just leave their phone more untouched.

Another main difference between the groups is during the weekend: as "alone time" increases, so does the touchscreen frequency. There seems to be no evident pattern displayed. To dive deeper into the data, we pass onto cohorts and their differences in smartphone usage.

*Fig. 6. **Lineplot**. Daily-hourly average by cohort (average N° of observations per user: 550). Users with somebody Vs alone or traveling*



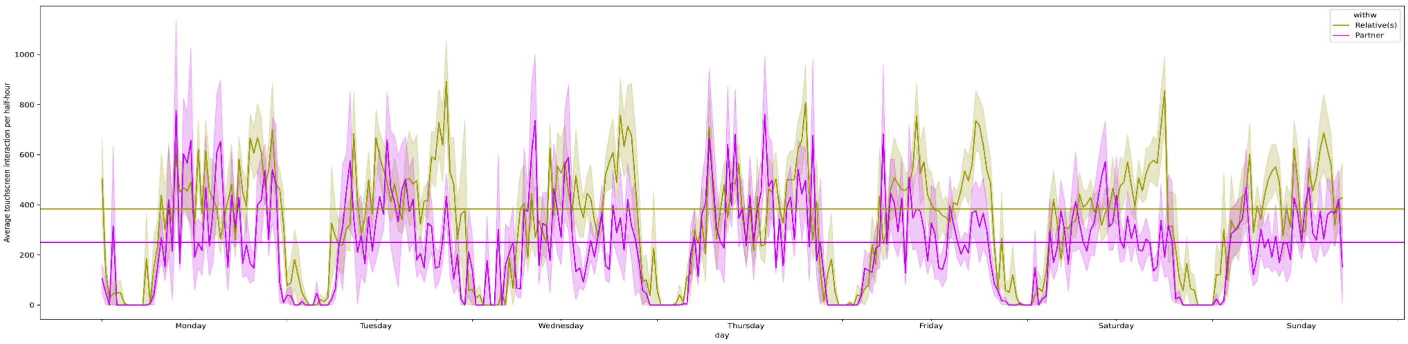
Note: By breaking down time by the hour, we can see overall the same cohort differences that were in the breakdown by weekday in a precedent version of the plot, but for simplicity purposes this version is more readable. The plots are comparable as they share the same *Y* and *X* scales.

On average, as shown in (6), the cohorts that are not behaving similarly to the others are 31+ year olds and 24 year olds, by actually using their phone more during social contexts compared to when they are by themselves. Though the differences are notable, it must be reported that only four users belong to the 31+ cohort, which is not a safe sample for generalization. The gap for smartphone screen usage between "alone time" and social time is the widest for cohorts of 19 and 20 year olds. On the contrary, there is very little difference in 20, 23 and 27-30 year olds.

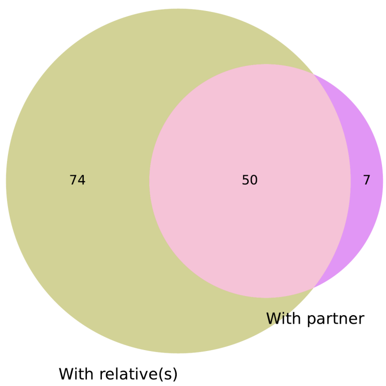
The remaining cohorts have an average difference, discernable on the hour, the day, and probably many other factors, such as the activity or the location.

*Fig. 7. **Lineplot**. Touchscreen with Partner Vs Relative(s) (resp. 6,186 vs 13,151)*

This visualization calls for some awareness regarding the composition of the sample.



The comparison in Fig. 7 is between two of the most significant groups examined in the Dunn test. there are very clear differences especially regarding the time of the day in which these two contexts occur. We must not assume that the same people who spend some of their time with their relatives are the same who spend some time with their partners: none of these visualizations are at the individual level, due to the many combinations possible - some may have a partner and live with their parents, others might not live with their parents but with their partner, other might not live with their parents nor with their parents but still spend time with both!



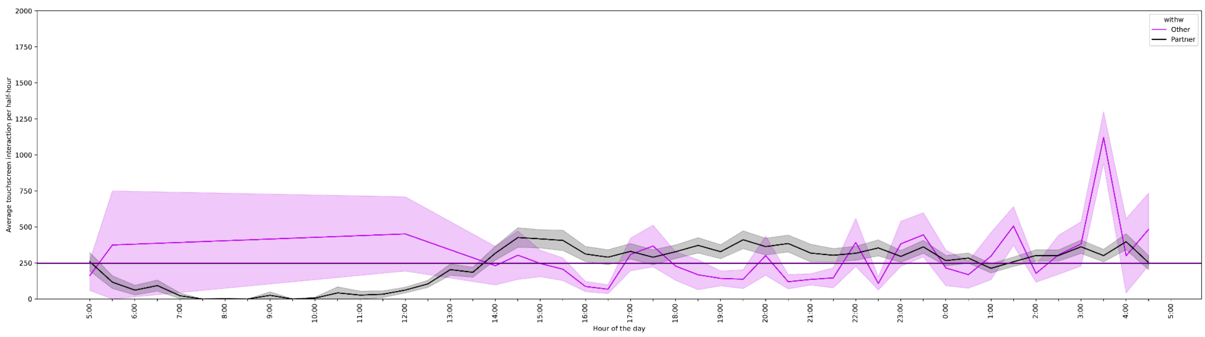
The user may live with their family, with their partner or by themselves, and those they live with influence greatly the data shown here, but usually younger cohorts happen to spend most of their time in their parent's house - and vice versa, older cohorts live with their partners. A Venn diagram is used to put in perspective how many

users[7] share having at least one experience with both contexts in the time of the observation.

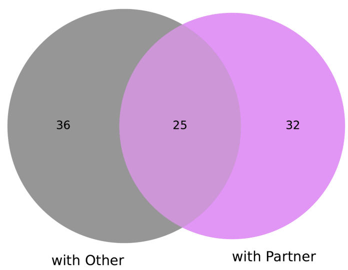
If a user is spending time with their relatives, they are more prone to using their phone more, although being in presence of a partner does not equate an out-of-the-ordinary use of the smartphone showing a significant difference between family members that are chosen (partners) versus family members that aren't.

As an addition to the last time breakdown, the worst comparison based on the Dunn test is when the screen touches are associated with "Partner" or with "Other". The latter option, "Other", may leave the interpretation of the social context rather confused, as there are many other options to choose from, such as relatives, friends, colleagues, classmates, travel companion. There could therefore be a bias in how the user receives the questionnaire. There also might be some similarities between spending time with a partner and spending time with "Other".

Fig. 8. ***Lineplot****. Other Vs Partner (resp. 340 vs 6,186)*



This is the only comparison between two types of social company that have almost the same average. However, this is the only similarity as the lack of observations makes an unclear distribution. This segment may be the only one that would require a different approach in the data collection design. The three main activities people who have spent time with a partner and are spending time with "Other" are: "Other"[8] (16.2%), Voluntary work / participatory activities (15.4%), Free Time Study (12.5%), likely these top three locations "Another indoor place" (30.8%), "Home, apartment / room" (18.7%), "Another outdoor place" (12.1%)



[7] This Venn diagram compares the sets of users that spent time with their relatives at least once and / or time with their partner at least once - the size of the circles represent the quantity of unique users, not the frequency of the events occurring.

[8] This further confuses the interpretation.

Discussion and conclusion

The approach to highly-dimensional categorical data in this report is to select the features based on their significance with respect to the continuous frequency of touchscreen use. Based on different methods, the features have different importance: for both a tuned Random Forest and Kruskal Wallis Test, the *activity* is the most important to predict the target variable, but they disagree with the second best predictor: one reports it as *whom* the user was with, the other indicates the *cohort*. Sex and department are generally not considered important. Categories belonging to the top three predictors indicate significant differences in touchscreen use: the activity, the company and the cohort actually represent particularly important factors. These factors are also featured in broader literature regarding the related phenomena, but in two different forms and research questions: the first, a "**situational**" influence on the use of smartphones, which is the product of an activity (social life, eating, studying, working) interacting with a social context, and the second being a "**life-long**" influence that is mediated by the cohort (or one's age) but may come from previous factors that are hardly quantifiable, such as the educational experience with technology, the *idioculture*[9] of the user's household diversity, and peers' influence. As an additional observation, ANOVA is not fit for this data, and its use is discouraged unless further preprocessing of the data is priorly conducted.

[9] This term references the Sociological field for the study of small group cultures, coined by Gary Alan Fine in 1979, and referred to as "a system of knowledge, beliefs, behaviors, and customs shared by members of an interacting group to which members can refer and employ as the basis of further interaction".

Bibliography and references

- Boumosleh, M. J., Jaalouk, D., (2017) Depression, anxiety, and smartphone addiction in university students- A cross sectional study. PLoS ONE 12(8): e0182239. https://doi.org/10.1371/journal.pone.0182239
- Fortunati, L. and Taipale, S. (2014), The advanced use of mobile phones in five European countries. The British Journal of Sociology, 65: 317-337. https://doi.org/10.1111/1468-4446.12075
- Humphreys, L., & Hardeman, H. (2021). Mobiles in public: Social interaction in a smartphone era. Mobile Media & Communication, 9(1), 103-127. https://doi.org/10.1177/2050157920927062
- Lillian Smyth, Kenneth I. Mavor, Michael J. Platow, Diana M. Grace & Katherine J. Reynolds (2015) Discipline social identification, study norms and learning approach in university students, Educational Psychology, 35:1, 53-72, DOI: 10.1080/01443410.2013.822962
- Thulin, E., & Vilhelmson, B. (2007). Mobiles everywhere: Youth, the mobile phone, and cihanges in everyday practice. *YOUNG*, *15*(3), 235-253. https://doi.org/10.1177/110330880701500302 Misra, S., Cheng, L., Genevie, J., & Yuan, M. (2016). The iPhone Effect: The Quality of In-Person Social Interactions in the Presence of Mobile Devices. *Environment and Behavior*, *48*(2), 275-298. https://doi.org/10.1177/0013916514539755 Ostertagová, E., Ostertag, O., & Kováč, J. (2014). Methodology and Application of the Kruskal-Wallis Test. Applied Mechanics and Materials, 611, 115–120. https://doi.org/10.4028/www.scientific.net/amm.611.115
- Thulin, E., Vilhelmson, B. & Schwanen, T., (2020) Absent Friends? Smartphones, Mediated Presence, and the Recoupling of Online Social Contact in Everyday Life, Annals of the American Association of Geographers, 110:1, 166-183, DOI: 10.1080/24694452.2019.1629868

References

- Code utilized in for this paper: https://github.com/FluveV/PhonePervasiveness/tree/main . It is commented and reviewed for reproducibility.
- Martin Cooper, et al., "Radio Telephone System", US Patent number 3,906,166; Filing date: 17 October 1973; Issue date: September 1975; Assignee Motorola