Mobile Social Media Usage and Academic Performance

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Abstract

Among the general population, students are especially sensitive to social media and smartphones because of their pervasiveness. Several studies have shown that there is a negative correlation between social media and academic performance since they can lead to behaviors that hurt students' careers, e.g., addictedness. However, these studies either focus on smartphones and social media addictedness or rely on surveys, which only provide approximate estimates. We propose to bridge this gap by *i)* parametrizing social media usage and academic performance, and *ii)* combining smartphones and time diaries to keep track of users' activities and their smartphone interaction. We apply our solution on the 72 students participating in the SmartUnitn project, which investigates students' time management and their academic performance. By analyzing the logs of social media apps on students' smartphones and by comparing them to students' credits and grades, we can provide a quantitative and qualitative estimate of negative and positive correlations. Our results show the negative impact of social media usage, distinguishing different influence patterns of social media on academic activities and also underline the need to control the smartphone usage in academic settings.

Keywords: Social media, Academic performance, Smartphone, Time diaries

1. Introduction

Social media have penetrated in the everyday life of Internet users, and the increasing pervasiveness of smartphones is only strengthening this phenomenon. Nowadays, these two technologies are intertwined, since smartphones are becoming more and more pervasive, especially in the student population.

In the literature, there is overwhelming evidence of the negative impact of social media (Paul et al., 2012), especially Facebook (Junco, 2012; Meier et al., 2016), and smartphone usage on academic performance (Lepp et al., 2015; Samaha & Hawi, 2016). These technologies combined lead to a series of behaviours that cause students to dedicate more time to them than actually studying. Usually, surveys are used to identify correlations between students' behaviour and their academic performances, coupled with scales that understand different metrics of students' behaviour. However, using surveys often fails to fully capture these behaviors. In fact, (Lee et al., 2017) finds that users underestimate their usage time by 40% than reported, while (Boase & Ling, 2013), although focusing only on SMS and calls, notes that self-reports suffer from low criterion validity and lead especially to overreporting usage, in contrast with (Lee et al., 2017). Furthermore, (Andrews et al., 2015) notes that users show great lack of awareness of the frequency with which they check their phone. On the other hand, works studying smartphone usage and social media tend to focus on addictedness (Lee et al., 2017, 2014). These studies investigate students since it is a sample of population very susceptible to smartphone penetration, but they do not attempt to correlate smartphone usage patterns to academic life. Thus there is a gap between this work on addictedness and sociological surveys on academic performance, since the former could be exploited to effectively corroborate the latter with usage logs.

We propose to bridge this gap via a systematic approach consisting in defining new metrics for representing social media usage and using smartphones to both track app usage and administer time diaries (Sorokin & Berger, 1939), a well known sociological tool for understanding people's time use. This innovative coupling allows us to isolate the time of specific activities related to academic performance and provide new insights on behavioural correlations.

We apply this approach on a subset of data about social media apps from the SmartUnitn project (Giunchiglia et al., 2017b), which aims at correlating the time management of students and their academic performances — this also covers how they manage their time when interacting with social media. We extract social media usage from students' smartphones during specific activities related to university life, i.e., studying and attending classes, and compare it with respect to their grades and credits obtained. Results show that there is a negative correlation between the use of social media and academic performance, with different patterns depending on the activity.

The remainder of this paper is organized as follows. Section 2 provides a review of the literature and the main issues with respect to sociological surveys and studies on addictedness. Section 3 describes our proposed solution, while Section 4 explains the dataset it is based on, i.e., SmartUnitn. Section 5 shows our results and provides their discussion. Finally, Section 6 concludes the paper, and illustrate implications and limitations of our work.

2. Literature Review

Studies using smartphones on students to understand the link between addictedness and usage usually divide them in two groups (potential addicts and non addicts) based the the Smartphone Addiction Scale (Kwon et al., 2013), which consists of ten items in a six-point Likert-type scale (1 = "I absolutely disagree", 6 = "I absolutely agree"). (Lee et al., 2014) used it on 95 students and then had them install the SmartLogger software to record specific events related to users' interactions with their phones, e.g., touch, text input and active/inactive events. The extracted patterns indicate that addict risk groups tended to spend more time on their apps, focusing on those that gave them instant gratifications, e.g., entertainment. Similarly, (Lee et al., 2017) had 35 students download an application that monitored their smartphone usage for 6 weeks. Results show that while messenger apps were the most used applications for both groups, addicts strongly preferred social media applications.

Students are also the main sample investigated in reality mining (Eagle & Pentland, 2006). In terms of social media, the Copenhagen Networks Study (Stopczynski et al., 2014) is currently collecting data on 1,000 students by coupling smartphone data with face-to-face interactions and Facebook usage; however, they do not consider these data in relation to students' academic performance. In terms of academic performance, the SmartGPA study (Wang et al., 2015) used data from the Student Life study (Wang et al., 2014), which analyzed the impact of workload on several mental and physical aspects of students' life, e.g. mood and sociability, of a class of 48 students across a 10 week term, to show that there is evidence of a link between the students' grades and their behaviour. However, (Wang et al., 2015) did not consider social media usage to analyze their impact on students' career, although this type of information was collected.

In the sociological community, studies show that there is a negative relation between social media usage and academic performance. For instance, (Rosen et al., 2013) investigated the behavior and settings of study for 263 students of different levels of education, i.e., middle school, high school, and university. Observers controlled students for 15 min and recorded their on-task and off-task behavior every minute. On average, students became distracted in less than 6 minutes before switching to technological distractions such as social media and texting. (Junco, 2012) focused on how Facebook use is related to academic performance, by surveying 1839 college students on their use of Facebook and then comparing it to their grades. The results indicate that a negative correlation exists between time spent on Facebook and grades. Overall, it appears that social media provide students with immediate pleasure in comparison to other activities such as studying or attending lessons (Jacobsen & Forste, 2011).

Much like social media, using smartphones also negatively affects academic performance (Al-Barashdi et al., 2015); indeed, social media are becoming more and more synonymous with usage with smartphones. In fact, (Jeong et al., 2016) notices that social networks can be used to predict smartphone addiction in users due to their pervasiveness and connectivity. These features of smartphones lead to multitasking (Lepp et al., 2015), i.e., the use of social media while doing something else, which is detrimental to the time dedicated to academic activities. (Lepp et al., 2015) conducted a survey on US college students, analyzing their notions of self-efficacy and self-regulation, i.e., how well they believe that they can attain their goals and how they can regulate and control themselves when using smartphones. Those students with low self-regulation turned out to be the one whose usage of smartphones affects their academic performance the most. In terms of demographics, (Al-Barashdi et al., 2015) suggests that gender and field of study may act as addiction predictors. From their review of the literature, it appears that males and humanities students tend to be more susceptible to smartphone addiction.

However, some research highlights how surveys used to establish these correlations may be unreliable, leading to an approximation of actual usage (Lee et al., 2017; Boase & Ling, 2013; Andrews et al., 2015). One reason is that surveys are based on aggregate data from 'stylized" questions (Juster & Stafford, 1985), e.g., "How many times a day on average do you check your smartphone?" (Gökçearslan et al., 2016), which force users to recall activities and finding an appropriate form of averaging (Kan & Pudney, 2008). On the other hand, works relying on smartphone data for analyzing usage tend to focus on addictedness on its own (Lee et al., 2017, 2014) or do not correlate usage patterns to academic performance (Wang et al., 2015).

3. Theory

Our proposed solution consists of two elements: *i)* defining metrics for capturing the smartphone usage patterns in terms of social media, illustrated in Section 3.1, and *ii)* employing together time diaries and smartphones to establish the correlation between social media usage and academic performance, described in Section 3.2. This second element provides the systematic aspect of our approach since it couples the two tools to overcome their respective limitations and produce more accurate results.

3.1. Parameters for social media usage and academic performance

To measure social media usage and academic performance, we define three different parameters: *i) social media*, *ii) usage* and *iii) academic performance.*

Social media (applications) are any technology used to share textual, image and audio content. We further divide social media applications, hence SM, in three categories:

- **Social network sites (SNS):** online platforms used by people to build social networks or social relations with other people, e.g., Facebook;
- **Instant messaging applications (IM):** online chats that offer real-time text transmission over the Internet, e.g., Whatsapp;
- **Browsers (Web):** software applications for retrieving, presenting and traversing information on the Internet, e.g., Chrome

This distinction allows capturing the fact that each type requires different usage patterns and threatens students' performances accordingly Junco (2012); Lepp et al. (2015). For instance, people use SNS for a longer period of time than IM Meier et al. (2016) and both negatively affect students' performance, while browsers may be used to access both academic and non-academic topics, e.g., going on Youtube for entertainment purposes vs going on Wikipedia for studying.

To represent and evaluate *the usage of social media*, we distinguish between three types of interactions between students and their smartphone applications:

1. $\bar{S}$: the average number of occurrences of social media app usage, i.e., *sessions* of students checking social media.;

2. $\bar{D}$: the average time of social media app usage (in seconds), i.e., the *duration* of the social media sessions, namely where any social media app is running ;
3. $\bar{I}$: the average time in between app usage (in seconds), namely when there is known human interaction (swiping/typing) with an app, i.e., the duration of the *inactivity* of the phone

Notice that $\bar{S}$ and $\bar{D}$ extend and provide further structure to the notion of frequency from Andrews et al. (2015), which only accounts for the former without considering its duration as a parameter.

We measure *academic performance* with two measures:

- **Grade Point Average (GPA):** the average of grade points students obtained during a semester. It represents the qualitative dimension of academic performance since it refers to the how well students perform;

- **Credito Formativo Universitario (CFU):** course credits obtained by students for each exam taken. They represent the quantitative dimension of academic performance since they refer to the progress of their university career.

Additionally, socio-demographic variables must be accounted for; in this work, following Al-Barashdi et al. (2015), students' faculties (scientific and humanities) are treated as socio-demographic variables to predict the effect of social media on academic performance.

3.2. Time diaries via smartphones

In terms of sociological survey tools, we employ *time diaries*. Time diaries are logs where respondents are asked to detail how they allocated their time during the day Sorokin & Berger (1939). These logs are tables divided into time intervals of 10 or 15 minutes Romano (2008), and provide information of time use in terms of activities performed, locations visited and people encountered during the 24-hour period Hellgren (2014).

Although time diaries also suffer from issues of reliability as all self-reports do Kan & Pudney (2008), they provide the following advantages:

1. Since respondents have to keep a log of their activities, time diaries allow us to acquire information not only on the average amount of time spent on different activities during a day but also the duration and frequency of each activity, together with their sequences;
2. Time diaries provide a systematic tool for also understanding spatial and social relations of users, which enriches and widens our scope of research;
3. Respondents do not need to provide average estimates in time diaries, which lessens the cognitive load while completing them Kan & Pudney (2008), while also reducing the possible mismatch between these answers given and the actual usage of smartphones.

In this work, we employ a time diary shown in previous work Giunchiglia et al. (2017a), which asks users three questions: *i)* “What are you doing?”, i.e., activities like “shopping”, *ii)* “Where are you?”, i.e., places like “home”, and *iii)* “Who is with you?”, i.e., social relations like “family”. The possible answers are a list of pre-defined labels, which minimizes coding, adapted from the ATUS time use survey Shelley (2005).

Smartphones can enhance time diaries by administering them to users, which they are then able to answer in (almost) real time, in addition to performing sensor collection, e.g., GPS, Bluetooth, call logs, and running applications, among others. These two functionalities of smartphones can be exploited to match any given triple of reported activity, location, and social relation with the status of the smartphone as a proxy of the actual user behavior. Our approach allows us to compare social media usage and academic performance, by matching those activities that are directly linked to academic outcomes, i.e., studying and attending lessons, together with the running applications, which include SM, at the time of the answer.

4. Method

We validate our proposed solution on the data from the SmartUnitn project, which belongs to a family of projects called ƧMAЯTRAMS[1] that leverages on smartphones to extract behavioural patterns from people and develop systems that assist users in their everyday life. The SmartUnitn project aims at investigating how students’ time allocations affects their academic performance.

The project relies on the i-Log mobile application (Zeni et al., 2014; Giunchiglia et al., 2017a) to provide the two functionalities needed from smartphones in our approach:

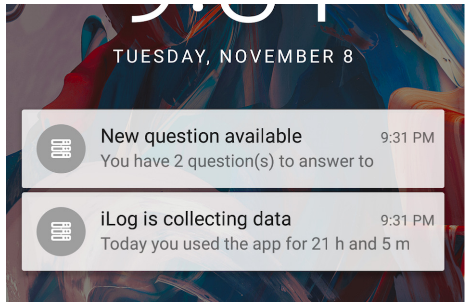
- **Data collection:** i-Log is designed to collect data from multiple sensors simultaneously, both hardware (e.g., GPS, accelerometer, gyroscope, among others) and software (e.g., in/out calls, applications running on the device). A dedicated backend infrastructure manages the tasks of synchronizing and storing the streams of data from the smartphones.

- **Time diaries:** i-Log can administer the time diary from (Giunchiglia et al., 2017a) as a question composed of three sub-question on activities, locations and social relations of students every 30 minutes. Every triple of questions can be answered within 150 minutes from its notification, with a maximum of 5 questions stacked in queue, otherwise it expires and treated as null. Questions appear as a silent notifications, shown in Figure 1, in order to avoid bothering students and disrupt their activities too much.

Based on two years of internal testing, i-Log has been designed to *ii)* be modular and adapt to each smartphone model, especially in terms of sensing

[1]See http://trams.disi.unitn.it for more information

Figure 1: I-Log notifications. The upper one shows the number of questions to be answered, while the bottom one notifies that the application is running



strategies for both smartphones and their internal sensors (which can greatly vary among different models) *ii)* to consume as little battery as possible, by devising sensor-dedicated energy consumption strategies and delegating all computation server-side, and *iii)* to ensure users' privacy from data collection to its analysis.

4.1. Participants

In the academic year 2015, 312 students enrolled at the University of Trento were contacted through a web survey to ask for their partecipation to the SmartUnitn project. 104 students fulfilled the three specific criteria: *i)* to have filled three university surveys in order to obtain their socio-demographic data, shown in Table 1, and other characteristics, e.g., psychological and time use related; *ii)* to attend lessons during the period of our project in order to describe their daily behavior during the university experience, and *iii)* to have an Android smartphone with an Android version 5.0.2 or higher.

Overall, 75 students accepted to participate but three of them declined during the project due to unexpected technological incompatibility with the i-Log. At the end, our final sample was composed by 72 students which reflects the general population of freshman year student of University of Trento in terms of gender and departments.

Table 1: Socio-demographics of students from our project

Gender		**Departments**		**Scholarship**	
Male	**Female**	**Scientific**	**Humanities**	**True**	**False**
61.1%	39.9%	56.9%	43.1%	37.5%	62.5%

The students were asked to attend an introductory presentation where they were presented with the aims of the project and how to use the application. If they wished to participate, after the presentation they signed a consent form, and then installed i-Log on their own smartphones. Users were informed about all aspects of the management of their personal information concerning privacy, from data collection to storage to processing. Furthermore, before starting the data collection, we obtained the approval from the ethical committee of our university.

4.2. Data collection

The project lasted two weeks. In the first one, students used i-Log to answer to time diaries while also having their data collected; during the second week, they were only required to have the application running for the collection of data.

We collected a total of 110 Gb of data from the 72 students for the whole duration of the project. The resulting dataset is a behavioural dataset that contains both time diaries answers and sensors data, thus exploiting sociological insights from the very beginning. It is also merged both with pre and post project surveys collecting socio-demographic characteristics of students, their time use habits asked through stylized-questions, some psychological traits measured by validated scales (i.e. pure procrastination scale or goal orientation scale) and academic performance data from the administrative office from our university.

4.3. Measures

In terms of our parameters, the SmartUnitn dataset provides the following data:

- **Social media:** 957 different applications are used among across all students. Within 32 SM apps, social networks are the most represented with 11 apps.
- **Usage:** Because of the Android operating system design, any application in the foreground keeps being logged for up to an hour, while i-Log collects running applications and the time at which their running every 5 seconds (on average). To obtain a more realistic understanding of usage, screen status information was added to filter out application logs recorded while students were not actually interacting with their phone. This operation results in a dataset of 135322 applications logging events covering the 7 days of the experiment during which the time diaries were administered.
- **Academic performance:** Information about GPA and CFU is provided from the University of Trento and it concerns the final performance of students at the end of their first academic year (September 2016).

Notice that the overall sample considered is 67 students and not 72 due to unexpected incompatibility of some students' smartphone operating system in providing the correct logs for running applications and for one outlier case in terms of number of CFU, most likely due to incorrect recording of that information from the administration, which made it impossible to understand his total amount of credits. Even though this student has logs of his apps usage, our analysis ignore these data.

5. Results and Discussion

There are three main results from our work concerning the social media usage of students and its correlation to academic performance. The first two concern the quantification of two dimensions of usage behaviour with respect to social media, i.e., $\bar{S}$, $\bar{D}$: *i)* the temporal distribution of the usage, which allows us to identify temporal patterns, shown in Section 5.1, and *ii)* the average usage mean, shown in Section 5.2. The third one is how $\bar{S}$, $\bar{D}$ and $\bar{I}$ are correlated to students' CFU and GPA, which is illustrated in Section 5.3.

5.1. Distribution

Figure 2 and Figure 3 report the distribution of $\bar{S}$ and $\bar{D}$ of social media usage during study, while Figure 4 and Figure 5 illustrate the distribution of the same parameters for attending lessons. These figures show 1-hour timeslots for every hour of the day and every day of the week, on the x and y axis respectively. Slots of empty spaces (in white) mean that no student was either studying or attending classes on that day during the specific time interval, while the darker the shade of color the higher the number of students using apps at that time. Notice that we do not show $\bar{I}$ because the distribution was entirely random.

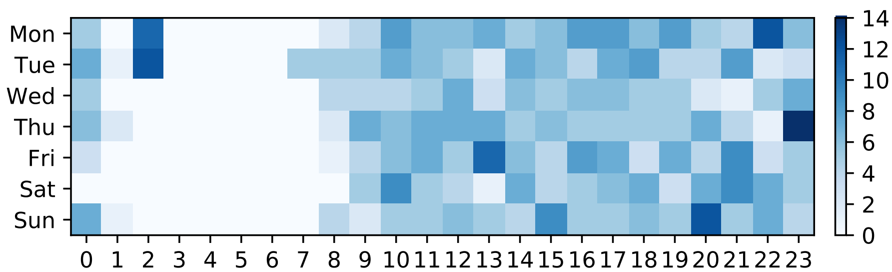


Figure 2: $\bar{S}$ of social media apps (SM) while studying

Figure 2 shows $\bar{S}$ while students reported that they were studying. Notice that the empty spaces concentrate during nighttime, as expected. Apart from few slots where there is a noticeable increase in usage, distribution through days and hours is mostly uniform. This means that students use social media while studying regardless of the time of the episode.

Figure 3 represents the $\bar{D}$ of all social media apps use while studying. This parameter increases in two different portions of the day: *i)* during nighttime, especially between midnight and 3 AM, and *ii)* early in the morning between 7 AM and 9 AM. Conversely, a decrease of $\bar{D}$ is underlined by the lighter area between 9 AM and 6 PM during weekdays.

In the University of Trento, lessons are concentrated during working days from 8 AM to 8 PM. Instances of classes during the weekend and outside this range are most likely outliers due to mistakes in reporting or possibly classes of non-academic subjects.

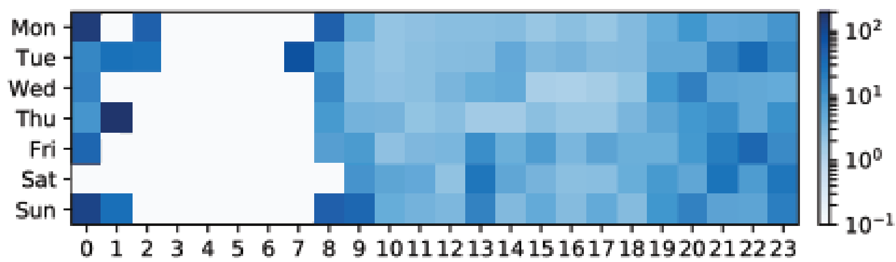


Figure 3: $\bar{D}$ of social media apps (SM) while studying

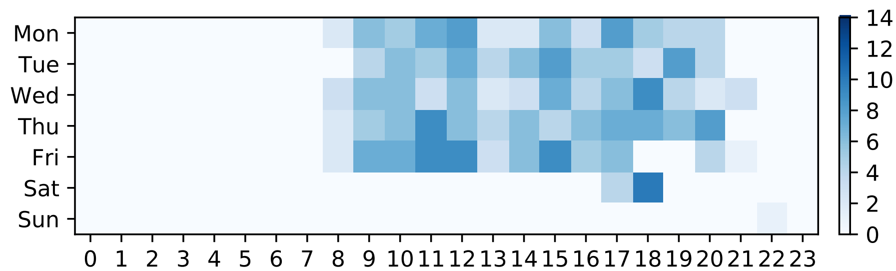


Figure 4: $\bar{S}$ of social media apps (SM) while attending lessons

Figure 4 shows that, similarly to Figure 2, the use of social media app ignores any actual time interval, although Friday appears to have a higher number of students checking SM apps.

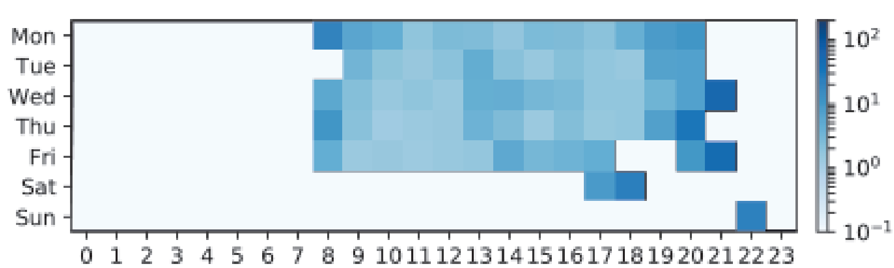


Figure 5: $\bar{D}$ of social media apps (SM) while attending lessons

Figure 5 shows the $\bar{D}$ of checking social media apps during lessons. The pattern that emerges suggests that students tend to stay connected longer early in the morning and then returning to similar $\bar{D}$ levels as the day goes by, especially during Friday afternoon. Overall, in terms of temporal distribution, all parameters tend to be uniformly distributed during the whole week, be they during studying or while attending lessons. This could be interpreted as an instance of the multitasking (Lepp et al., 2015) behavior permeating the everyday life of students.

5.2. *Average mean*

We propose an analysis of the mean values of $\bar{S}$, $\bar{D}$, and $\bar{I}$ for all apps, focusing on SM apps, with respect to activities in general, Table 2, while students were studying, Table 2b, and attending lessons, Table 2c. For each table, rows represent the type of activity (general, studying or attending lessons), the type of apps considered (all apps, SM apps as a whole, SNS, IM, and Web) and their respective parameters, while columns represent the parameters mean usage values (Mean), their standard deviation (Sd) and the number of students (N).

Table 2: All social media usage with respect to our variables (parameters and apps) during:

(a) General activities

			Mean	Sd	N
General	All	$\bar{S}$	1975,55	798,31	67
		$\bar{D}$	47,67	50,79	67
		$\bar{I}$	236,37	136	67
	SM	$\bar{S}$	664,25	360,50	67
		$\bar{D}$	69,13	22,65	67
		$\bar{I}$	157,80	143,65	67
	SNS	$\bar{S}$	160,91	149,28	67
		$\bar{D}$	140,25	96,28	66
		$\bar{I}$	79,57	103,21	66
	IM	$\bar{S}$	440	282,58	67
		$\bar{D}$	43,77	20,24	67
		$\bar{I}$	180,89	155,24	67
	Web	$\bar{S}$	63,43	64,18	67
		$\bar{D}$	98,71	40,46	60
		$\bar{I}$	57,21	68,92	60

(b) Studying

			Mean	Sd	N
Study	All	$\bar{S}$	296,37	228,99	67
		$\bar{D}$	44,52	20,88	64
		$\bar{I}$	198,64	148,06	64
	SM	$\bar{S}$	108,44	96,94	67
		$\bar{D}$	70,57	34,13	64
		$\bar{I}$	121,69	97,38	64
	SNS	$\bar{S}$	23,91	32,21	67
		$\bar{D}$	121,37	100,29	57
		$\bar{I}$	94,99	224,91	57
	IM	$\bar{S}$	73,74	70,52	67
		$\bar{D}$	49,86	30,57	64
		$\bar{I}$	140,30	127,88	64
	Web	$\bar{S}$	10,79	16,06	67
		$\bar{D}$	93,04	60,98	49
		$\bar{I}$	58,57	104,83	49

(c) Attending lessons

			Mean	Sd	N
Lesson	All	$\bar{S}$	269,97	176,64	67
		$\bar{D}$	36,23	17,29	66
		$\bar{I}$	167,07	122,23	66
	SM	$\bar{S}$	87,71	67,37	67
		$\bar{D}$	57,03	28,82	65
		$\bar{I}$	134,21	203,93	65
	SNS	$\bar{S}$	19,76	26,28	67
		$\bar{D}$	117,50	111,11	57
		$\bar{I}$	66,65	87,27	57
	IM	$\bar{S}$	57,22	48,98	67
		$\bar{D}$	36,65	25,74	65
		$\bar{I}$	144,80	200,07	65
	Web	$\bar{S}$	10,73	14,31	67
		$\bar{D}$	90,38	73,59	51
		$\bar{I}$	87,82	280,39	51

For general activities, $\bar{S}$ appears to be the most relevant parameter both for all apps and SM apps (1975.55, SD 798.31 and 664.25, SD 360.50), followed by $\bar{I}$ and $\bar{D}$. Within SM apps, IM are the most checked type of apps, with $\bar{S}$ being almost 4 times the other apps (440, SD 282.58), but also the one with the highest value for $\bar{I}$ (180.89, SD 155,24), while SNS sessions last the longest ($\bar{D}$ of 120.25). This general pattern is also true for reported usage of smartphones both while studying and attending lessons, although with some differences. Firstly, SM apps are checked more frequently and for longer periods of time while studying than during lessons (higher values of $\bar{S}$ and $\bar{D}$ for SM and each app type). Notice that in the case of $\bar{D}$ of SNS and Web the values are nonetheless very close, unlike IM, with 49.86, SD 30.57 for studying vs 36.65, SD 25.74 for attending lessons. Secondly, while $\bar{I}$ is lower during studying in terms of SM (121.69, SD 97.38), its values for IM apps are almost equal: for study, the mean is 140.30 seconds (SD 127.88) and for lesson it is 144.80 seconds (SD 200.07). Overall, these findings suggest the following:

- On average, students check SM apps more frequently and for longer periods while studying than attending lessons (higher $\bar{S}$ and $\bar{D}$), but while in class these sessions are more done in a longer window of time (higher $\bar{I}$).

Table 3: Correlations of all apps and social media apps, with academic performance, based on overall activities plus studying and attending lessons

			CFU									GPA								
			All	**Hum.**	**Sci.**	**F**	**M**	**Sci.\F**	**Hum.\F**	**Sci.\M**	**Hum.\M**	**All**	**Hum.**	**Sci.**	**F**	**M**	**Sci.\F**	**Hum.\F**	**Sci.\M**	**Hum.\M**
General	**All**	$\bar{S}$	-0.09 (68)	0.01 (30)	-0.2 (38)	0.05 (28)	-0.2 (40)	0.33 (10)	0.11 (16)	-0.41 (21)	-0.05 (14)	-0.05 (68)	-0.2 (30)	0.02 (38)	-0.13 (28)	-0.0 (40)	0.29 (10)	-0.31 (16)	-0.24 (21)	-0.0 (14)
		$\bar{D}$	0.01 (68)	-0.04 (30)	-0.0 (38)	-0.01 (28)	-0.02 (40)	-0.25 (10)	-0.11 (16)	0.05 (21)	-0.15 (14)	0.07 (68)	0.07 (30)	-0.06 (38)	0.08 (28)	-0.03 (40)	-0.4 (10)	0.05 (16)	0.06 (21)	-0.11 (14)
		$\bar{I}$	0.17 (67)	-0.02 (29)	0.36* (38)	0.1 (27)	0.27 (40)	0.13 (10)	-0.07 (15)	0.41 (21)	-0.02 (14)	0.16 (67)	0.14 (29)	0.19* (38)	0.14 (27)	0.21 (40)	-0.69 (10)	0.2 (15)	0.48 (21)	-0.04 (14)
	SM	$\bar{S}$	-0.16 (67)	-0.02 (29)	-0.26 (38)	-0.01 (27)	-0.25 (40)	0.05 (10)	0.04 (15)	-0.49* (21)	-0.02 (14)	-0.1 (67)	-0.32 (29)	0.0 (38)	-0.07 (27)	-0.1 (40)	0.23 (10)	-0.33 (15)	-0.3* (21)	-0.25 (14)
		$\bar{D}$	-0.04 (67)	-0.23 (29)	0.07 (38)	-0.26 (27)	0.1 (40)	-0.13 (10)	-0.36 (15)	0.15 (21)	-0.05 (14)	0.03 (67)	0.11 (29)	0.0 (38)	-0.28 (27)	0.19 (40)	-0.7 (10)	-0.02 (15)	0.19 (21)	0.31 (14)
		$\bar{I}$	0.06 (67)	0.01 (29)	0.09 (38)	0.17 (27)	-0.02 (40)	0.19 (10)	0.02 (15)	0.04 (21)	-0.2 (14)	0.07 (67)	0.08 (29)	0.05 (38)	0.14 (27)	0.04 (40)	-0.37 (10)	0.1 (15)	0.15 (21)	-0.09 (14)
	SNS	$\bar{S}$	-0.26* (67)	-0.1 (29)	-0.46** (38)	-0.03 (27)	-0.41** (40)	-0.29 (10)	0.08 (15)	-0.5* (21)	-0.26 (14)	-0.19 (67)	-0.18 (29)	-0.31** (38)	-0.26 (27)	-0.16** (40)	-0.23 (10)	-0.37 (15)	-0.32* (21)	0.12 (14)
		$\bar{D}$	0.01 (66)	-0.29 (28)	0.2 (38)	-0.08 (26)	0.05 (40)	0.06 (10)	-0.42 (14)	0.2 (21)	-0.24 (14)	0.05 (66)	-0.02 (28)	0.06 (38)	-0.03 (26)	0.09 (40)	-0.64 (10)	0.08 (14)	0.08 (21)	-0.03 (14)
		$\bar{I}$	-0.18 (66)	-0.16 (28)	-0.19 (38)	0.02 (26)	-0.26 (40)	-0.42 (10)	-0.26 (14)	-0.28 (21)	-0.09 (14)	-0.16 (66)	-0.11 (28)	-0.19 (38)	-0.06 (26)	-0.17 (40)	-0.33 (10)	-0.22 (14)	-0.2 (21)	-0.02 (14)
	IM	$\bar{S}$	-0.1 (67)	0.03 (29)	-0.16 (38)	-0.01 (27)	-0.16 (40)	0.11 (10)	0.03 (15)	-0.4 (21)	0.08 (14)	-0.07 (67)	-0.29 (29)	0.06 (38)	0.03 (27)	-0.11 (40)	0.27 (10)	-0.17 (15)	-0.27 (21)	-0.38 (14)
		$\bar{D}$	-0.06 (67)	-0.01 (29)	-0.05 (38)	-0.21 (27)	-0.02 (40)	0.06 (10)	-0.75** (15)	-0.08 (21)	0.38 (14)	-0.04 (67)	0.08 (29)	-0.04 (38)	-0.32 (27)	0.03 (40)	-0.34 (10)	-0.3** (15)	0.04 (21)	0.25 (14)
		$\bar{I}$	0.12 (67)	0.06 (29)	0.15 (38)	0.22 (27)	0.06 (40)	0.22 (10)	0.1 (15)	0.12 (21)	-0.11 (14)	0.12 (67)	0.12 (29)	0.11 (38)	0.18 (27)	0.1 (40)	-0.34 (10)	0.19 (15)	0.23 (21)	-0.05 (14)
	Web	$\bar{S}$	0.13 (67)	0.01 (29)	0.2 (38)	0.01 (27)	0.2 (40)	0.14 (10)	-0.11 (15)	0.22 (21)	0.1 (14)	0.19 (67)	-0.06 (29)	0.38 (38)	0.08 (27)	0.26 (40)	0.26 (10)	-0.09 (15)	0.28 (21)	-0.07 (14)
		$\bar{D}$	-0.03 (60)	-0.59** (26)	0.21 (34)	-0.15 (24)	0.05 (36)	0.26 (9)	-0.5 (13)	0.23 (18)	-0.68* (13)	-0.0 (60)	-0.15** (26)	0.09 (34)	-0.23 (24)	0.14 (36)	-0.19 (9)	-0.23 (13)	0.08 (18)	-0.0* (13)
		$\bar{I}$	0.12 (60)	-0.02 (26)	0.2 (34)	-0.0 (24)	0.18 (36)	-0.19 (9)	0.05 (13)	0.3 (18)	-0.22 (13)	0.2 (60)	0.19 (26)	0.25 (34)	0.31 (24)	0.17 (36)	0.06 (9)	0.44 (13)	0.38 (18)	-0.18 (13)
Study	**All**	$\bar{S}$	0.02 (67)	0.11 (29)	-0.17 (38)	0.14 (27)	-0.06 (40)	0.34 (10)	-0.04 (15)	-0.24 (21)	0.23 (14)	-0.04 (67)	-0.12 (29)	-0.12 (38)	-0.09 (27)	-0.04 (40)	0.17 (10)	-0.45 (15)	-0.11 (21)	0.06 (14)
		$\bar{D}$	-0.12 (65)	-0.33 (28)	-0.09 (37)	-0.06 (27)	-0.2 (38)	-0.05 (10)	-0.12 (15)	0.01 (20)	-0.67* (13)	0.02 (65)	0.01 (28)	-0.08 (37)	0.15 (27)	-0.1 (38)	-0.17 (10)	0.26 (15)	0.04 (20)	-0.29* (13)
		$\bar{I}$	0.23 (65)	-0.02 (28)	0.4* (37)	0.11 (27)	0.36* (38)	-0.15 (10)	-0.02 (15)	0.52* (20)	-0.16 (13)	0.26* (65)	0.29 (28)	0.28* (37)	0.15 (27)	0.37* (38)	-0.51 (10)	0.33 (15)	0.57* (20)	0.21 (13)
	SM	$\bar{S}$	-0.03 (67)	0.16 (29)	-0.26 (38)	0.07 (27)	-0.11 (40)	-0.07 (10)	0.12 (15)	-0.31 (21)	0.21 (14)	-0.08 (67)	-0.16 (29)	-0.14 (38)	-0.05 (27)	-0.11 (40)	0.02 (10)	-0.33 (15)	-0.18 (21)	-0.06 (14)
		$\bar{D}$	-0.07 (64)	-0.41* (28)	0.02 (36)	-0.29 (26)	0.08 (38)	-0.19 (10)	-0.62* (15)	0.17 (20)	-0.14 (13)	-0.04 (64)	-0.14* (28)	-0.06 (36)	-0.24 (26)	0.06 (38)	-0.4 (10)	-0.12* (15)	0.17 (20)	-0.08 (13)
		$\bar{I}$	0.14 (64)	-0.17 (28)	0.3 (36)	0.24 (26)	0.15 (38)	0.27 (10)	0.08 (15)	0.33 (20)	-0.34 (13)	0.11 (64)	0.13 (28)	0.18 (36)	0.06 (26)	0.2 (38)	-0.22 (10)	0.25 (15)	0.44 (20)	0.12 (13)
	SNS	$\bar{S}$	-0.11 (67)	0.02 (29)	-0.49** (38)	0.08 (27)	-0.22 (40)	-0.46 (10)	0.09 (15)	-0.48* (21)	-0.03 (14)	-0.15 (67)	-0.17 (29)	-0.41** (38)	-0.22 (27)	-0.12 (40)	-0.54 (10)	-0.39 (15)	-0.33* (21)	0.01 (14)
		$\bar{D}$	0.17 (57)	-0.01 (25)	0.23 (32)	-0.09 (23)	0.29 (34)	0.08 (9)	-0.38 (13)	0.34 (18)	0.28 (12)	0.02 (57)	-0.13 (25)	0.07 (32)	-0.18 (23)	0.12 (34)	-0.36 (9)	-0.08 (13)	0.23 (18)	-0.06 (12)
		$\bar{I}$	-0.01 (57)	-0.03 (25)	0.11 (32)	0.03 (23)	0.01 (34)	0.25 (9)	0.32 (13)	0.09 (18)	-0.25 (12)	0.0 (57)	-0.12 (25)	0.13 (32)	-0.08 (23)	0.07 (34)	-0.11 (9)	0.18 (13)	0.14 (18)	-0.24 (12)
	IM	$\bar{S}$	-0.01 (67)	0.22 (29)	-0.19 (38)	0.04 (27)	-0.06 (40)	-0.0 (10)	0.12 (15)	-0.27 (21)	0.32 (14)	-0.05 (67)	-0.12 (29)	-0.07 (38)	-0.0 (27)	-0.1 (40)	0.09 (10)	-0.21 (15)	-0.17 (21)	-0.06 (14)
		$\bar{D}$	-0.06 (64)	-0.29 (28)	0.02 (36)	-0.22 (26)	0.04 (38)	-0.0 (10)	-0.79*** (15)	-0.03 (20)	0.22 (13)	-0.08 (64)	-0.08 (28)	-0.08 (36)	-0.3 (26)	0.01 (38)	-0.33 (10)	-0.2*** (15)	0.02 (20)	0.01 (13)
		$\bar{I}$	0.29* (64)	-0.12 (28)	0.46** (36)	0.29 (26)	0.33* (38)	0.22 (10)	0.26 (15)	0.56** (20)	-0.33 (13)	0.23 (64)	0.17 (28)	0.3** (36)	0.06 (26)	0.35* (38)	-0.18 (10)	0.24 (15)	0.61** (20)	0.23 (13)
	Web	$\bar{S}$	0.07 (67)	0.07 (29)	0.03 (38)	0.08 (27)	0.07 (40)	-0.14 (10)	-0.05 (15)	0.13 (21)	0.12 (14)	0.03 (67)	-0.07 (29)	0.06 (38)	0.09 (27)	-0.01 (40)	-0.05 (10)	-0.05 (15)	0.19 (21)	-0.17 (14)
		$\bar{D}$	-0.18 (49)	-0.43* (23)	-0.15 (26)	-0.3 (20)	-0.1 (29)	-0.07 (7)	-0.54 (13)	-0.12 (16)	-0.26 (10)	0.09 (49)	-0.07* (23)	0.13 (26)	0.12 (20)	0.07 (29)	0.43 (7)	-0.07 (13)	0.1 (16)	0.1 (10)
		$\bar{I}$	0.05 (49)	-0.17 (23)	0.19 (26)	-0.13 (20)	0.16 (29)	-0.5 (7)	-0.01 (13)	0.39 (16)	-0.39 (10)	0.08 (49)	0.21 (23)	-0.02 (26)	0.15 (20)	0.06 (29)	-0.49 (7)	0.43 (13)	0.1 (16)	-0.02 (10)
Lesson	**All**	$\bar{S}$	0.02 (67)	-0.06 (29)	0.1 (38)	-0.05 (27)	0.07 (40)	0.4 (10)	-0.18 (15)	-0.11 (21)	0.09 (14)	0.03 (67)	-0.26 (29)	0.24 (38)	-0.25 (27)	0.17 (40)	0.36 (10)	-0.62 (15)	-0.07 (21)	0.06 (14)
		$\bar{D}$	-0.11 (66)	-0.37 (29)	0.05 (37)	-0.14 (27)	-0.08 (39)	-0.01 (10)	-0.5 (15)	-0.01 (20)	-0.22 (14)	-0.08 (66)	-0.17 (29)	0.06 (37)	-0.25 (27)	0.06 (39)	-0.2 (10)	-0.41 (15)	0.16 (20)	0.07 (14)
		$\bar{I}$	0.31* (66)	0.0 (29)	0.44** (37)	0.33 (27)	0.32* (39)	0.39 (10)	0.15 (15)	0.47* (20)	-0.26 (14)	0.4*** (66)	0.42 (29)	0.41** (37)	0.42 (27)	0.41* (39)	-0.09 (10)	0.64 (15)	0.65* (20)	0.14 (14)
	SM	$\bar{S}$	-0.02 (67)	0.12 (29)	-0.02 (38)	-0.01 (27)	-0.03 (40)	0.19 (10)	0.21 (15)	-0.24 (21)	0.06 (14)	-0.01 (67)	-0.3 (29)	0.17 (38)	-0.17 (27)	0.07 (40)	0.27 (10)	-0.49 (15)	-0.15 (21)	-0.14 (14)
		$\bar{D}$	-0.21 (65)	-0.26 (29)	-0.15 (36)	-0.47* (26)	-0.11 (39)	-0.38 (9)	-0.45 (15)	-0.12 (20)	-0.07 (14)	-0.11 (65)	0.01 (29)	-0.11 (36)	-0.51* (26)	0.05 (39)	-0.56 (9)	-0.35 (15)	-0.01 (20)	0.31 (14)
		$\bar{I}$	0.16 (65)	-0.13 (29)	0.24 (36)	0.28 (26)	0.16 (39)	0.59 (9)	0.02 (15)	0.23 (20)	-0.24 (14)	0.2 (65)	0.11 (29)	0.29 (36)	-0.11 (26)	0.31 (39)	-0.36 (9)	0.0 (15)	0.44 (20)	0.22 (14)
	SNS	$\bar{S}$	-0.24 (67)	-0.0 (29)	-0.34* (38)	-0.16 (27)	-0.3 (40)	-0.33 (10)	0.02 (15)	-0.37 (21)	-0.09 (14)	-0.21 (67)	-0.21 (29)	-0.2* (38)	-0.46 (27)	-0.08 (40)	-0.3 (10)	-0.55 (15)	-0.23 (21)	0.43 (14)
		$\bar{D}$	-0.24 (57)	-0.45* (26)	-0.11 (31)	-0.55** (22)	-0.08 (35)	-0.38 (8)	-0.84*** (12)	-0.03 (17)	-0.18 (14)	-0.13 (57)	-0.15* (26)	-0.2 (31)	-0.33** (22)	-0.01 (35)	-0.52 (8)	-0.35*** (12)	-0.13 (17)	0.01 (14)
		$\bar{I}$	0.07 (57)	-0.08 (26)	0.21 (31)	0.2 (22)	-0.02 (35)	0.08 (8)	0.21 (12)	0.01 (17)	-0.21 (14)	0.05 (57)	0.09 (26)	0.08 (31)	-0.13 (22)	0.2 (35)	-0.07 (8)	-0.17 (12)	0.1 (17)	0.31 (14)
	IM	$\bar{S}$	0.08 (67)	0.13 (29)	0.1 (38)	0.07 (27)	0.08 (40)	0.38 (10)	0.2 (15)	-0.1 (21)	0.12 (14)	0.05 (67)	-0.27 (29)	0.25 (38)	0.01 (27)	0.07 (40)	0.45 (10)	-0.26 (15)	-0.08 (21)	-0.28 (14)
		$\bar{D}$	-0.05 (65)	0.02 (29)	-0.04 (36)	-0.2 (26)	-0.01 (39)	0.04 (9)	-0.42 (15)	-0.08 (20)	0.4 (14)	-0.03 (65)	0.03 (29)	-0.01 (36)	-0.29 (26)	0.05 (39)	-0.3 (9)	-0.23 (15)	0.02 (20)	0.26 (14)
		$\bar{I}$	0.14 (65)	-0.11 (29)	0.23 (36)	0.22 (26)	0.15 (39)	0.5 (9)	-0.04 (15)	0.21 (20)	-0.17 (14)	0.18 (65)	0.08 (29)	0.27 (36)	-0.14 (26)	0.29 (39)	-0.4 (9)	0.01 (15)	0.43 (20)	0.14 (14)
	Web	$\bar{S}$	0.09 (67)	0.11 (29)	0.12 (38)	0.04 (27)	0.12 (40)	0.04 (10)	0.33 (15)	0.08 (21)	-0.07 (14)	0.15 (67)	-0.01 (29)	0.27 (38)	0.05 (27)	0.22 (40)	0.13 (10)	0.13 (15)	0.1 (21)	-0.1 (14)
		$\bar{D}$	-0.15 (51)	-0.32 (22)	-0.03 (29)	-0.09 (21)	-0.18 (30)	0.34 (7)	-0.5 (12)	-0.32 (15)	-0.28 (10)	-0.19 (51)	-0.37 (22)	-0.06 (29)	-0.34 (21)	-0.14 (30)	-0.38 (7)	-0.25 (12)	-0.13 (15)	-0.48 (10)
		$\bar{I}$	0.22 (51)	0.29 (22)	0.27 (29)	0.45* (21)	0.22 (30)	0.75 (7)	0.4 (12)	0.27 (15)	-0.51 (10)	0.3* (51)	0.51 (22)	0.36 (29)	0.52* (21)	0.33 (30)	0.43 (7)	0.57 (12)	0.52 (15)	0.33 (10)

Notes: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$; Hum.=Humanities; Sci.=Scientific; F=Female; G=Gender; (N)=N of students; the gradient of color represents the result significance.

- Within SM apps for both studying and attending lessons, IM apps are the most checked but with the longest window of time in between sessions, while SNS apps are the ones with the highest duration of usage.

5.3. Social media usage vs GPA and CFU

Table 3 shows how $\bar{S}$, $\bar{D}$ and $\bar{I}$ are correlated to students' CFU and GPA by using Pearson's correlation.

In Table 3 the darker the color of the cells whose parameters, considering columns and rows, obtain a significant value with respect to the correlation coefficient, the higher the value significance (i.e., higher p value). Rows represent $\bar{S}$, $\bar{D}$ and $\bar{I}$ for the combination of application type and activities from the Section 5. Columns represent the sociodemographic variables considered and the academic performance indexes, GPA and CFU. The socio-demographics are gender, faculties (distinguishing between scientific and humanities), and the combination of the two, i.e., male and female students from either faculty.

We expect a negative correlation in an increase of $\bar{S}$ and $\bar{D}$, since they would imply more smartphone usage and hence less time dedicated to academic activities. Conversely, we expect $\bar{I}$ to be positively correlated with academic activity since it would indicate less time dedicated to smartphones.

5.3.1. Significant values of social media usage

Table 4a, Table 4b and Table 4c summarize the occurrence of significant values for $\bar{S}$, $\bar{D}$, and $\bar{I}$. Columns indicate the number of significant values, divided according to their p value, and their total amount, while rows represent the type of activity (general, studying or attending lessons), the type of apps considered (all apps, SM apps as a whole, SNS, IM, and Web), their respective parameters, and their sum accounting for both the number of values and their significance.

Table 4a shows that during general activities $\bar{S}$ and $\bar{D}$ have a relatively close amount of significant correlations (9 and 6, respectively), while $\bar{I}$ has only 2. Moreover, $\bar{S}$ of SNS is especially significant, reaching 7 values (4 with $p < .01$).

If we look at the same values for studying and attending lessons, Table 4b and Table 4c respectively, studying provides more occurrences than attending lessons (28 vs 21), but with similar occurrences of values per significance.

Moreover, $\bar{I}$ is the parameter with the most occurrences of significant values for both activities, with a total of 25, followed by $\bar{D}$ with 18 and finally $\bar{S}$, only 6. Within SM, IM provides the most significant values for studying, concentrated on $\bar{I}$; however, there are no IM values for lessons, which means that IM provides no correlations in this case. On the other hand, SNS provide the most values for establishing correlations in lessons, especially for $\bar{D}$.

Overall, these findings suggest that our parameters for usage and social media plus the time diary answers for academic activities allow us to effectively underline different patterns of SM app influence. Moreover:

- While studying, the average duration of usage of IM apps ($\bar{D}$ with negative p values) is the most harmful for academic performance; however, the

Table 4: Number of significant value occurrences from our variables in:

(a) General activities

			$p < .05$	$p < .01$	$p < .001$	**Total**
General	**All**	$\bar{S}$	0	0	0	0
		$\bar{D}$	0	0	0	0
		$\bar{I}$	2	0	0	2
		Total	2	0	0	2
	SM	$\bar{S}$	2	0	0	2
		$\bar{D}$	0	0	0	0
		$\bar{I}$	0	0	0	0
		Total	2	0	0	2
	SNS	$\bar{S}$	3	4	0	7
		$\bar{D}$	0	0	0	0
		$\bar{I}$	0	0	0	0
		Total	3	4	0	7
	IM	$\bar{S}$	0	0	0	0
		$\bar{D}$	0	2	0	0
		$\bar{I}$	0	0	0	0
		Total	0	2	0	2
	Web	$\bar{S}$	0	0	0	0
		$\bar{D}$	2	2	0	4
		$\bar{I}$	0	0	0	0
		Total	2	2	0	4
	Sum	$\bar{S}$	5	4	0	9
		$\bar{D}$	2	4	0	6
		$\bar{I}$	2	0	0	2
		Total	9	8	0	17

(b) Studying

			$p < .05$	$p < .01$	$p < .001$	**Total**
Study	**All**	$\bar{S}$	0	0	0	0
		$\bar{D}$	2	0	0	2
		$\bar{I}$	7	0	0	7
		Total	9	0	0	9
	SM	$\bar{S}$	0	0	0	0
		$\bar{D}$	4	0	0	4
		$\bar{I}$	0	0	0	0
		Total	4	0	0	4
	SNS	$\bar{S}$	2	2	0	4
		$\bar{D}$	0	0	0	0
		$\bar{I}$	0	0	0	0
		Total	2	2	0	4
	IM	$\bar{S}$	0	0	0	0
		$\bar{D}$	0	0	2	2
		$\bar{I}$	3	4	0	7
		Total	3	4	2	9
	Web	$\bar{S}$	0	0	0	0
		$\bar{D}$	2	0	0	2
		$\bar{I}$	0	0	0	0
		Total	2	0	0	2
	Sum	$\bar{S}$	2	2	0	4
		$\bar{D}$	8	0	2	10
		$\bar{I}$	10	4	0	14
		Total	20	6	2	28

(c) Attending lessons

			$p < .05$	$p < .01$	$p < .001$	**Total**
Lesson	**All**	$\bar{S}$	0	0	0	0
		$\bar{D}$	0	0	0	0
		$\bar{I}$	5	2	1	8
		Total	5	2	1	8
	SM	$\bar{S}$	0	0	0	0
		$\bar{D}$	2	0	0	2
		$\bar{I}$	0	0	0	0
		Total	2	0	0	2
	SNS	$\bar{S}$	2	0	0	2
		$\bar{D}$	6	0	0	6
		$\bar{I}$	0	0	0	0
		Total	8	0	0	8
	IM	$\bar{S}$	0	0	0	0
		$\bar{D}$	0	0	0	0
		$\bar{I}$	0	0	0	0
		Total	0	0	0	0
	Web	$\bar{S}$	0	0	0	0
		$\bar{D}$	0	0	0	0
		$\bar{I}$	3	0	0	3
		Total	3	0	0	3
	Sum	$\bar{S}$	2	0	0	2
		$\bar{D}$	8	0	0	8
		$\bar{I}$	8	2	1	11
		Total	18	2	1	21

longer students avoid them ($\bar{I}$ with positive p values) the higher their performances.

- The average duration of usage ($\bar{D}$ with negative p values) and the average occurrences of checking ($\bar{S}$ with negative p values) SNS while attending lessons negatively affect students' academic performance

5.3.2. Significant values for CFU and GPA

Table 5 and Table 6 show the total occurrences of significant values between our variables and the CFU and GPA, i.e., 33 for both. Columns indicate the type of variable considered: all, faculty (humanities and scientific), gender (females and males), the combination of the two (females and males in scientific and humanities faculties) and their sum. Rows represent the number of significant values, divided according to their p value, and their total amount.

On average, the influence of SM apps both on CFU and GPA appears to be stronger for scientific students than for students from humanities (7 vs 4), while gender differences seem to be less important and are almost equally distributed in our sample. In addition, distinguishing within each faculty suggests that being either a male student enrolled in a scientific faculty or being a female from humanities are the most "at risk" groups of a decrease of academic performance.

Table 5 shows that without considering any demographics, there is very little correlation between social media apps usage and CFU. There are three positive occurrences, i.e., $\bar{S}$ of SNS usage in general (-.26, $p < 0.05$), $\bar{I}$ of IM apps while studying (0.29, $p < 0.05$)and $\bar{I}$ of all the apps during lessons (0.28, $p < 0.05$). Taking into account students' field of study, while for humanities

Table 5: Number of significant correlations for CFU

	CFU									
	All	**Hum.**	**Sci.**	**F**	**M**	**Sci.\F**	**Hum.\F**	**Sci.\M**	**Hum.\M**	**Sum**
$p < .05$	3	3	2	2	3	0	1	5	2	21
$p < .01$	0	1	5	1	1	0	1	1	0	10
$p < .001$	0	0	0	0	0	0	2	0	0	2
Tot	3	4	7	3	4	0	4	6	2	33

Table 6: Number of significant correlations for GPA

	GPA									
	All	**Hum.**	**Sci.**	**F**	**M**	**Sci.\F**	**Hum.\F**	**Sci.\M**	**Hum.\M**	**Sum**
$p < .05$	1	3	3	2	3	0	1	5	2	20
$p < .01$	1	1	4	1	1	0	1	1	0	10
$p < .001$	1	0	0	0	0	0	2	0	0	3
Tot	3	4	7	3	4	0	4	6	2	33

the $\bar{D}$ parameter is related to a lower number of CFU, for scientific students, $\bar{S}$ and $\bar{I}$ of SM apps tends to be more associated with increased CFU. Considering gender, SM negatively affect CFU from females especially during lessons: $\bar{D}$ of SM (-0.47, $p < 0.05$) and SNS (-0.55, $p < 0.01$) plus $\bar{I}$ of browser apps (0.45, $p < 0.05$); this effect is even stronger for females in humanities, with $\bar{D}$ of SM reaching -0.84 ($p < 0.001$). For males, the pattern is less clear but the parameter that has a stronger negative correlation on CFU is $\bar{S}$ of SNS during general activities (-0.41, $p < 0.01$).

Table 6 shows that, if we control for GPA without including demographics, we find the same trend of CFU results: $\bar{I}$ of all apps while both studying (0.26, $p < 0.05$) and attending lessons (0.40, $p < 0.001$), and specifically $\bar{I}$ of Web apps during lessons, are positively associated with their GPA. Taking into account students' field of study, app usage significantly affects GPA while studying, with stronger effects for scientific students than humanities. Moreover, scientific students' GPA increases if they have higher $\bar{I}$ for all the apps (0.28, $p < 0.05$) and for IM apps (0.30, $p < 0.05$) and it decreases with higher level of $\bar{S}$ for SNS apps (-0.41, $p < 0.01$) while studying. Once again, also for GPA, the negative influence of social media app usage for females occurs while attending lessons. Indeed, $\bar{D}$ of social media apps in general (-0.51, $p < 0.05$) and of SNS in particular (-0.33, $p < 0.01$) affects females performance especially while they are in the classroom. Overall, these findings suggest that:

- There appear to be no major differences between males and female in terms of correlation of SM app usage and academic performance.
- Academic performance of scientific students is more affected by their SM usage than students from humanities. While this is an interesting finding, its causes are unclear and require further research.
- $\bar{S}$ and $\bar{D}$ are always correlated with lower performance both for GPA and for CFU while longer inactive periods ($\bar{I}$) are positively associated with them.

6. Conclusions and Limitations

In this paper, we proposed to overcome the current limitations of the state of the art in linking students' usage of social media on smartphones by coupling smartphones and time diaries, to then be able to match reports of time use with actual logs of SM apps. We proposed a method which aims to overcome the limits of both types of data (i.e., time diary answers and sensor data) in order to improve the informative power of our results. Specifically, based on the sample from the SmartUnitn project, we could corroborate the finding of sociological literature by using three parameters that pinpointed behavioral patterns that could either hurt academic performance, e.g., constantly message while studying or staying on SNS while in class, or improve it, e.g., limiting IM usage. Overall, our results confirm our hypothesis that social media apps usage during academic activities (in terms of sessions and duration) is informative with respect to their negative association with students' academic performance. Indeed, it is more so than considering their general use without activity distinction, in addition to their faculties. In particular, the parameters of the use of social media apps show a similar association both for CFU and GPA measures but the coefficients are bigger for CFU. This means that the effect of the use of social media apps is stronger on the progress of students' career than on the quality of their study. Moreover, the results show that the inactivity during studying or attending lessons affects more positively the academic performance of scientific students than humanities students. Finally, by taking into account both gender and department variables, the groups that show the worst performance are females in humanities in comparison of males in humanities and males in scientific fields than females, especially when considering studying. This last evidence could be possibly due to the size of the sample of females in scientific fields, which we will confirm on future works. These results would be impossible to know without the integration of both methods of data collection.

Our results highlighted the unlikeliness of students at high risk of smartphone addiction of achieving distinctive academic performance especially when we observe the use of social media apps during studying or lessons attending activities. It can distract students from academic success with possible repercussions in terms of the productivity level of the society. Administrators and academic staff should be aware of how their students are using technology, also by taking into account its detrimental effect on their academic performance, and they should sensitize students to a wise use of smartphone especially during those activities strictly related to their academic performance. Open discussions or tutoring services may help them learn better strategies for managing their time and their academic workload.

Nonetheless, there two main limitations in our work. The first one is the relatively small window of time considered, i.e., two weeks, compared to other studies in computational social sciences, e.g., 10 weeks in SmartGPA (Wang et al., 2015) and almost one year in the Copenhagen Networks Study Karpinski et al. (2013). However, notice that one week of time diaries is considerably more than the usual amount of days recorded in sociology, which is usually limited to two days (one weekday and one weekend) (Romano, 2008), and thus allowed us a bigger time window to extract patterns from. The second one is the number of students in our sample. While it is considerably smaller than other studies in sociology, e.g., 263 students in (Rosen et al., 2013) and 1839 students in (Junco, 2012), our sample is still larger than other works in the area of computational social sciences, e.g., 48 students in SmartGPA (Wang et al., 2015) and 35 students in (Lee et al., 2017). Although we are aware of the possible limitations of this study in terms of sample and window of time covered, they will be addressed in the next iteration of SmartUnitn to be carried out in March of 2018, by also detailing more the type of students' faculty, given how relevant it is in light of our results.

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