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Mobile Social Media and Academic Performance

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Abstract. Recent studies have shown that there is a negative correlation between social media and academic performance, since they can lead to behaviours that hurt students' careers, e.g., addictedness. However, these studies either focus on smartphones and social media addictedness *per se* or rely on sociological surveys, which only provide approximate estimations of the phenomena. 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. By analyzing the logs of social media apps while studying and attending lessons, and comparing them to students' GPA, we can quantify negative and positive correlations via smartphones.

Keywords: Social media; Academic performance; Smartphones; Time diaries

1 Introduction

Nowadays, social media and smartphones are intertwined, since smartphones are becoming more and more pervasive, especially in the student population.

In sociological literature, there is evidence of the negative impact of social media [9,16,17] and smartphone usage on academic performance [15,20]. For instance, [19] analyzed the behaviour and settings of study for 263 students, showing that students became distracted in less than 6 minutes before switching to technological distractions, e.g., social media. [8] notices that social networks can be used to predict smartphone addiction in users. In fact, smartphones lead to disruptive behaviors like multitasking [6], i.e., the use of social media while doing something else. [15] finds that the usage of smartphones from students with low self regulation affects their academic performance the most. [1] suggests that, among different demographics, gender and field of study, especially males and humanities students, may act as addiction predictors.

Studies using smartphones on students to understand the link between addictedness and usage generally divide them in two groups (addicts and non addicts) based on the Smartphone Addiction Scale [12]. [14] extracted behavioural patterns from 95 students' smartphones, noting that addict risk groups tend to spend more time on apps providing instant gratifications. Similarly, [13] finds that, in a sample of 35 students monitored for 6 weeks, addicts strongly prefer social media. Students are also the main sample investigated in reality mining [4]. In terms of academic performance, the SmartGPA study [23] analyzed the impact of workload on several mental and physical aspects of students' life, e.g. mood, and sociability, to show that there is evidence of a link between students' GPA and their behaviour.

However, some research highlights how surveys used in sociology may be unreliable, leading to an approximation of actual usage [13,3,2]. One reason is that surveys are based on aggregate data from 'stylized" questions [10], e.g., "How many times a day on average do you check your smartphone?" [6], which force users to recall activities and find an appropriate form of averaging [11]. On the other hand, works analyzing smartphone usage tend to focus on addictedness on its own [13,14] or do not correlate usage patterns to academic performance. In fact, [23] ignored social media usage, although this information was collected.

Thus there is a gap between work on addictedness and sociological surveys on academic performance. We bridge this gap by defining new metrics for representing social media usage and using smartphones to track usage and administer time diaries [22], a sociological tool for understanding people's time use. This innovative coupling allows us to isolate the time of specific activities related to academic performances and provide new insights on behavioural correlations.

We apply this approach on a subset of data about social media apps from the SmartUnitn project, which aims at correlating the time management of students and their academic performances. We extract social media usage from students' smartphones during specific academic activities, i.e., studying and attending lessons, and compare it with their GPA as a measure for academic performance. 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 describes our solution, while Section 3 explains the SmartUnitn dataset. Section 4 and Section 5 show our results on the correlation between social media usage and academic performance. Finally, Section 6 concludes the paper.

2 Social media usage and academic performance

Our proposed solution consists of two elements: *i)* employing together time diaries and smartphones to establish the correlation between social media usage and academic performance and *ii)* defining metrics for capturing the smartphone usage patterns in terms of social media.

Time diaries are logs where respondents are asked to detail how they allocated their time in terms of of activities performed, locations visited and people encountered during their day [7]. In this work, we employ a time diary, shown in previous work [5], 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 [21]. Smartphones can enhance time diaries by administering them to users, which then can answer them in (almost) real time, while also 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.

To represent 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 media, e.g., text and videos. We further divide social media applications, hence SM, in three categories: *Social Network Sites* (hence SNS), e.g., Facebook, *Instant Messaging Applications* (hence IM), e.g., Whatsapp, and *Browsers* (hence Web), e.g., Chrome. This distinction allows to capture the fact that each type of social media requires different usage patterns and threatens students performances accordingly [9,15]. For instance, people use SNS for a longer period of time than IM [16] and both negatively affect students' performance, while browsers may be used to access both academic and non academic topics, e.g., going on Youtube vs going on Wikipedia.

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, namely when there is known human interaction (swiping/typing) with an app (in seconds), 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 [2], which only accounts for frequency itself without considering its duration as parameter.

We represent *academic performance* with *Grade Point Average (GPA)*, i.e., the average of grade points a student obtained in a semester. Additionally, socio-demographic variables must be accounted for; in this paper, following [1], students' faculties (scientific and humanities) are treated as socio-demographic variables to predict the effect of social media on academic performance.

3 The experiment

We validate our proposed solution on the data from the SmartUnitn project, which belongs to a family of projects called ƧMAЯTRAMS[3] that leverages on

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

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 [24,5] 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, application 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 [5] 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.

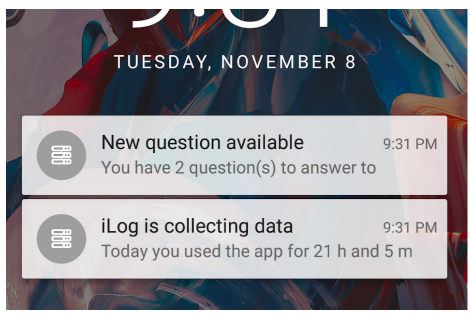

Fig. 1: I-Log notifications. The upper one shows the number of questions to be answered, while the bottom one notifies that the application running.

In SmartUnitn, 72 students used i-Log to answer to time diaries while also having their data collected for the first week; during the second week, they were only required to have the application running for the collection of data. 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) [18], and thus allowed us a bigger time window to extract patterns from. Furthermore, the number of students is larger than other works in the area of computational social sciences, e.g., almost doubling SmartGPA [23] sample of 48 students. Given the involvement of students, the project is approved by the ethical committee of the University of Trento.

The SmartUnitn dataset amounts to 110 Gb, containing behavioural data from smartphones merged with socio-demographic characteristics of students obtained both through surveys and academic performance data provided by the University of Trento.

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

- **Social media:** There are 32 SM apps used across our sample.
- **Usage:** To obtain usage information, i-Log collects running applications and the time at which their running every 5 seconds (on average). They are integrated with screen status information, since, due to Android operating system design, any application in the foreground keeps being logged for up to an hour; this allows us to achieve a more realistic usage result. We obtain a dataset of 135322 applications logging events covering the 7 days of the experiment during which the time diaries were administered.
- **Academic performance:** Students' GPA is provided from the University of Trento. It concerns the final performance of students at the end of their first academic year (September 2016).

4 Quantifying social media usage

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 1a, while students were studying, Table 1b, and attending lessons, Table 1c. 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).

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 $\bar{S}$ 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 for IM, with 49.86, sd 30.57 for studying vs 36.65, sd 25.74 for attending lessons. Secondly, while $\bar{I}$ is lower when students are 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 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 $\bar{I}$).
- 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.

Table 1: All social media usage with respect to our variables (parameters and apps) during:

(a) General activities

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

(b) Studying

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

(c) Attending lessons

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

5 Social media usage vs GPA

Table 2 shows how $\bar{S}$, $\bar{D}$ and $\bar{I}$ are correlated to students' GPA by using Pearson's correlation because of the continuous nature of the variables. In Table 2, 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 (p value). Rows represent $\bar{S}$, $\bar{D}$ and $\bar{I}$ for the combination of application type and activities from the Section 4. Columns represent the socio-demographic variables considered and the GPA. 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 faculties.

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 a higher value of $\bar{I}$ to be positively correlated with academic activity, since it would indicate less time dedicated to smartphones.

5.1 Significant values of social media usage

Table 3a, Table 3b and Table 3c summarize the occurrence of significant values for $\bar{S}$, $\bar{D}$, and $\bar{I}$. Columns indicate the amount 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 amount of values and their significance.

Table 3a shows that during general activities $\bar{S}$ and $\bar{D}$ have a relatively close amount of significant correlations (4 and 3, respectively), while $\bar{I}$ has only 1.

Table 2: Correlations of all apps and social media apps, with academic performance, based on overall activities plus studying and attending lessons.

			GPA								
			All	Hum.	Sci.	F	M	Sci.\F	Hum.\F	Sci.\M	Hum.\M
General	All	$\bar{S}$	-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)
		$\bar{D}$	0.07 (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)
		$\bar{I}$	0.16 (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	$\bar{S}$	-0.1 (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)
		$\bar{D}$	0.03 (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)
		$\bar{I}$	0.07 (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	$\bar{S}$	-0.19 (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)
		$\bar{D}$	0.05 (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)
		$\bar{I}$	-0.16 (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	$\bar{S}$	-0.07 (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)
		$\bar{D}$	-0.04 (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)	0.12 (29)	0.11 (38)	0.18 (27)	0.1 (40)	-0.34 (10)	0.19 (15)	0.23 (21)	-0.05 (14)
	Web	$\bar{S}$	0.19 (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)
		$\bar{D}$	-0.0 (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)
		$\bar{I}$	0.2 (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	$\bar{S}$	-0.04 (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)
		$\bar{D}$	0.02 (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)
		$\bar{I}$	0.26* (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	$\bar{S}$	-0.08 (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)
		$\bar{D}$	-0.04 (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)
		$\bar{I}$	0.11 (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	$\bar{S}$	-0.15 (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)
		$\bar{D}$	0.02 (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)
		$\bar{I}$	0.0 (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	$\bar{S}$	-0.05 (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)
		$\bar{D}$	-0.08 (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)
		$\bar{I}$	0.23 (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	$\bar{S}$	0.03 (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)
		$\bar{D}$	0.09 (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)
		$\bar{I}$	0.08 (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	$\bar{S}$	0.03 (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)
		$\bar{D}$	-0.08 (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)
		$\bar{I}$	0.4*** (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	$\bar{S}$	-0.01 (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)
		$\bar{D}$	-0.11 (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)
		$\bar{I}$	0.2 (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	$\bar{S}$	-0.21 (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)
		$\bar{D}$	-0.13 (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)
		$\bar{I}$	0.05 (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	$\bar{S}$	0.05 (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)
		$\bar{D}$	-0.03 (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)
		$\bar{I}$	0.18 (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	$\bar{S}$	0.15 (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)
		$\bar{D}$	-0.19 (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)
		$\bar{I}$	0.3* (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

Moreover, $\bar{S}$ of SNS is the parameter with the most significant values, reaching 3 values (2 with $p < .01$).

Table 3b and Table 3c indicate that studying provides slightly more occurrences than attending lessons (14 vs 11), 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 13, followed by $\bar{D}$ with 9 and finally $\bar{S}$, only 3. Within SM, IM has the most significant values for studying (mainly for $\bar{I}$); however, there are no IM values for lessons. 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 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 longer students avoid them ($\bar{I}$ with positive p values) the higher their performances.

Table 3: Number of significant value occurrences from our variables in:

(a) General activities

			$p < .05$	$p < .01$	$p < .001$	**Total**
General	**All**	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	0	0	0	0
		$\bar{\mathbf{I}}$	1	0	0	1
		Total	1	0	0	1
	SM	$\bar{\mathbf{S}}$	1	0	0	1
		$\bar{\mathbf{D}}$	0	0	0	0
		$\bar{\mathbf{I}}$	0	0	0	0
		Total	1	0	0	1
	SNS	$\bar{\mathbf{S}}$	1	2	0	3
		$\bar{\mathbf{D}}$	0	0	0	0
		$\bar{\mathbf{I}}$	0	0	0	0
		Total	1	2	0	3
	IM	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	0	1	0	1
		$\bar{\mathbf{I}}$	0	0	0	0
		Total	0	1	0	1
	Web	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	1	1	0	2
		$\bar{\mathbf{I}}$	0	0	0	0
		Total	1	1	0	2
	Sum	$\bar{\mathbf{S}}$	2	2	0	4
		$\bar{\mathbf{D}}$	1	2	0	3
		$\bar{\mathbf{I}}$	1	0	0	1
		Total	4	4	0	8

(b) Studying

			$p < .05$	$p < .01$	$p < .001$	**Total**
Study	**All**	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	1	0	0	1
		$\bar{\mathbf{I}}$	4	0	0	4
		Total	5	0	0	5
	SM	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	2	0	0	2
		$\bar{\mathbf{I}}$	0	0	0	0
		Total	2	0	0	2
	SNS	$\bar{\mathbf{S}}$	1	1	0	2
		$\bar{\mathbf{D}}$	0	0	0	0
		$\bar{\mathbf{I}}$	0	0	0	0
		Total	1	1	0	2
	IM	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	0	0	1	1
		$\bar{\mathbf{I}}$	1	2	0	3
		Total	1	2	1	4
	Web	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	1	0	0	1
		$\bar{\mathbf{I}}$	0	0	0	0
		Total	1	0	0	1
	Sum	$\bar{\mathbf{S}}$	1	1	0	2
		$\bar{\mathbf{D}}$	4	0	1	5
		$\bar{\mathbf{I}}$	5	2	0	7
		Total	10	3	1	14

(c) Attending lessons

			$p < .05$	$p < .01$	$p < .001$	**Total**
Lesson	**All**	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	0	0	0	0
		$\bar{\mathbf{I}}$	2	1	1	4
		Total	2	1	1	4
	SM	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	1	0	0	1
		$\bar{\mathbf{I}}$	0	0	0	0
		Total	1	0	0	1
	SNS	$\bar{\mathbf{S}}$	1	0	0	1
		$\bar{\mathbf{D}}$	1	1	1	3
		$\bar{\mathbf{I}}$	0	0	0	0
		Total	2	1	1	4
	IM	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	0	0	0	0
		$\bar{\mathbf{I}}$	0	0	0	0
		Total	0	0	0	0
	Web	$\bar{\mathbf{S}}$	0	0	0	0
		$\bar{\mathbf{D}}$	0	0	0	0
		$\bar{\mathbf{I}}$	2	0	0	2
		Total	2	0	0	2
	Sum	$\bar{\mathbf{S}}$	1	0	0	1
		$\bar{\mathbf{D}}$	2	1	1	4
		$\bar{\mathbf{I}}$	4	1	1	6
		Total	7	2	2	11

– 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

5.2 Significant values for GPA

Table 4 show the total occurrences of significant values between our variables GPA, i.e., 33. 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 amount of significant values, divided according to their p value, and their total amount.

On average, the influence of SM apps on GPA appears to be stronger for scientific students than for students from humanities (7 vs 4), while gender differences seem to be less important, being 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 4 shows that, if we control for GPA without including demographics, $\bar{I}$ of all apps while both studying (0.26, $p < 0.05$) and attending lessons (0.40, $p <$

Table 4: 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

0.001) 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. 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:

- While there is no major difference in terms of gender, academic performance of scientific students is more affected by their SM usage than students from humanities. Although this is an interesting finding, its causes are unclear and require further research.
- $\bar{S}$ and $\bar{D}$ are always correlated with lower GPA, while inactivity ($\bar{I}$) shows positive correlations.

6 Conclusions

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. Based on the sample from the SmartUnitn project, we could corroborate the finding of sociological literature by using three parameters that pinpointed behavioural patterns that could either hurt academic performance, e.g., constantly messaging while studying or staying on SNS while in class, or improve, e.g., limiting IM usage.

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