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Cell phone usage and academic performance: An experiment

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ABSTRACT

This paper makes use of an experiment to test the relationship between the actual average time students spend using their smartphones per day and academic performance. Differently from previous studies that rely on self-reporting mobile phone usage data, which tends to significantly underestimate the time spent by students at their phones, we employed Apps (namely 'Moment' and 'App Usage Tracker') to effectively measure actual usage. Collecting data from 43 students at Fundação Getúlio Vargas (FGV), a business school from São Paulo, Brazil, our analysis yielded a significant negative relationship between total time spent using smartphones and academic performance, after controlling for known predictors of performance such as self-efficacy and past academic results. Each 100 min spent using the device on average per day corresponded to a reduction in a student's position at the school's ranking of 6.3 points, in a range from 0 to nearly 100. Moreover, if we consider usage during class time only (as opposed to during free time and weekends), the effect was almost twice as high. The magnitude of the effect found is alarming. Thus, this study brings new evidence of the potential harm of excessive smartphone use and should be useful for educators and other academic stakeholders interested in the subject of the impact of technology on students' performance.

1. Introduction

In recent years, access to affordable digital devices rose substantially. The share of Americans that own smartphones is now 77%, up from just 35% in 2011. Smartphones are nearly ubiquitous among younger adults, with 92% of Americans aged 18- to 29-year-olds owning one (Pew Research Center report, 2017).

As a result, the use of cellphones[1] and tablets becomes everyday more frequent at schools and universities, not only in spare time, but also during class. Even though the use of technology, especially portable devices, may provide a set of tools that potentially leverage learning, research (e.g., Barkley & Lepp, 2013) has shown that these technologies are primarily perceived as a leisure tool, not as an educational one. Therefore, if cellphones are commonly used in class for purposes unrelated to the discipline, it is likely that students may be distracted during lectures or activities, as they often overestimate their ability to multitask (Ophir, Nass, & Wagner, 2009), which could eventually lead to academic underperformance.

Technology use is highly related to multitasking, particularly for students, once they often keep connected to social media and their friends through texting apps while studying and doing homework. Indeed, several studies (notably Jacobsen & Forste, 2011; Junco & Cotton, 2012) have confirmed that students report being connected to more than one social media while performing

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[1] The terms 'cellphone' and 'smartphone' are used in this paper interchangeably, meaning handheld personal computers with a mobile operating system and/or access to the Internet.

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academic tasks. Notwithstanding, Wood et al. (2012) found that multitasking in any of the analyzed technologies (emailing, texting and Facebook) was negatively correlated to the capability to learn effectively, demonstrated by lower test scores.

In their recent review of the literature, Chen and Yan (2016) covered one hundred and four studies that explicitly examined mobile phone multitasking while learning, exploring the topic in multiple fronts. Many studies, however, concentrated on the cognitive and psychological mechanisms through which multitasking might impair learning or on how to prevent from the negative effects of mobile multitasking. The authors conclude that few studies have explicitly investigated the relationship between mobile phone multitasking and learning outcome (Chen & Yan, 2016). Despite increasing penetration of technology across universities around the world in the last decade, its academic effects, particularly over students' learning, are not yet fully understood. This article intends to offer a contribution on this front.

1.1. Cellphone usage and academic outcomes

Recent studies have attempted investigate whether there is any adverse implication of high cellphone usage in learning (Junco, 2012a,b; Junco & Cotten, 2012; Murphy & Manzanares, 2008; Mayer & Moreno, 2003; Rosen, Carrier, & Cheever, 2013; and Wood et al., 2012), finding evidence that there is indeed a negative correlation between digital portable devices usage and academic performance.

Most past studies, however, have focused on analyzing the impact of specific applications (e.g., texting, social media, gaming, etc.) as opposed to general usage. In particular, the impact of social media has been extensively documented across the world. In every case, the amount of time spent on social media was negatively related to academic performance. Many studies have tested for the same variables in a variety of social media settings (Facebook, Twitter, Whatsapp), but we highlight Kirschner and Karpinski (2010), which notably found that, for a sample of 102 undergraduate and 117 graduate students at a large US university, heavy Facebook users had a lower self-reported GPAs, and Junco (2012a, 2012b), which concluded that Facebook usage contributed to lower actual GPAs for a large sample of US college students.

Jacobsen and Forste (2011) studied specifically the impacts of texting and calling in self-reported GPA scores for a sample of 1026 first-year North American university students and found a negative relationship between the variables. Hong, Chiu, and Hong (2012) found similar conclusions when analyzing texting and calling effects among Taiwanese female students.

Isolated effects of uses other than texting and calling and social media have been analyzed less frequently. Most conclusions, especially when testing for internet usage and gaming impacts, have pointed to a negative correlation between their use and academic performance. Jackson, von Eye, Witt, Zhao, and Fitzgerald (2011) associated lower GPAs with heavy gaming, for example, while Chen and Peng (2008) related lower levels of internet use with better academic performance for a sample of 49,609 junior students from 156 universities.

1.2. Limitations of current literature

All the above-mentioned studies have either failed to involve all possible applications of current smartphones – meaning that they have focused on specific uses, such as texting and calling –, or/and have collected their data through surveys, lacking more precise methods to accurately quantify the actual amount of time spent on smartphones during classes.

In particular, relying on self-reported cellphone usage time might carry significant bias for several reasons. Firstly, most people give imprecise information, because it is rather difficult in practice to estimate how much of one's day was dedicated to any particular activity. Secondly, when self-reporting usage time, there is little assurance that the concept of usage is the same among participants. While one may believe that only calling and texting amount as cellphone usage, for instance, another may consider gaming, or surfing the internet. More importantly, there is evidence that students tend to significantly underestimate the number of times they access their phones. Duncan, Hoekstra, and Wilcox (2012) found that, on average, students report an access rate of three times per class while the actual observed rate is close to stunning twenty-one times.

In order to attempt to eliminate the above-mentioned bias of self-reporting data, we monitored directly the smartphones from students at Fundação Getúlio Vargas, a business school in São Paulo, Brazil, through downloaded applications (Apps) which retrieved data of each cellphone's actual daily usage. This data was then voluntarily shared by students with the experiment's developers, and was used, together with demographic and official academic performance information, to assess the relevance and impact of cellphone usage in academic results. Comparing self-reported cellphone usage time assessed in our survey to the actual usage time obtained through the monitoring applications, the latter was on average 48.5% higher, confirming the hypothesis of significant bias in self-reported data.

Another limitation of the existing literature that investigates cellphone usage in real-world classrooms settings is that studies are typically correlational, making it difficult to determine causal relations. Worse academic performance may be caused by cellphone usage but it could also be that students who are worse off academically spend more time on their cellphones. In particular, previous research (e.g., Schunk, 1989) suggested that students with better time-management skills obtain better results, and this characteristic could also help them regulate cellphone usage. Both variables may be correlated due to a common cause: effectiveness in regulating focus and attention.

Some interesting controlled studies have been conducted to try to determine the mechanisms of causation (Rosen et al., 2013; Wood et al., 2012), but they inevitably face limitations of their own as a result of their laboratory settings (e.g., external validity). In particular, in reviewing and comparing laboratory and real-world classroom experiments, Carrillo and Subrahmanyam (2015) observed that while laboratory studies tended to find that multitasking had negavite effects on learners' efficiency but not comprehension, classroom studies showed negative effects on learning and recall (Chen & Yan, 2016).

In order to attempt to address the issue of correlation and causation within the real-world classroom setting, we have introduced two control variables in our model, namely (i.) past academic performance (measured as the student's performance on a broad objective university entrance exam) and (ii.) "self-efficacy" beliefs (Pajares, 1996), which portray one's belief in his or her ability to plan and execute the necessary tasks to perform well and succeed in whichever goals he or she might have. As a consequence of this belief, students reporting higher self-efficacy scores are usually more perseverant and more inclined to learn (Schunk, 1984, 1989). Hence, self-efficacy measures are positively correlated to most academic performance results, such as grades, homework, assignments, and class positioning (Multon, Brown, & Lent, 1991; Pajares, 1996).

Two frameworks of self-efficacy have become notorious because of their predicting accuracy (Pajares, 1996). The first is the self-efficacy for self-regulated learning (SE:SRL), which describes a student's ability to regulate his or her own path towards academic success, which includes avoiding distractions, overcoming obstacles, accomplishing necessary tasks and creating appropriate learning environments. The second is the self-efficacy for academic achievement (SE:AA), which involves one's ability to learn contents from specific fields of knowledge, such as science and math.

Lepp, Barkley, and Karpinski (2015) have published the only study we know of that sought to relate cellphone usage and academic performance while controlling for known predictors such as SE:SRL and SE:AA. After sampling 536 undergraduate students and controlling for demographic variables, self-efficacy for self-regulated learning (SE:SRLL), self-efficacy for academic achievement (SE:AA) and actual high school GPAs, the study concluded that there was a negative relation between cellphone use and college GPAs (proxy for academic performance). However, their study was based on surveys to determine the intensity of cellphone usage, which according to their own data collected from a group of 21 students, had only a moderate correlation (50%) to actual cellphone usage obtained through their cellphone's records.

1.3. Proposition of the study

In sum, while the available literature surrounding the effects of technology over academic performance offers some guidance towards the expected results for the present study, it is clear that some specific gaps have not been filled yet. First, it is necessary to address the smartphone as an integrated platform for a variety of applications, extending beyond traditional uses such as texting and calling. Moreover, even though several analyses have come to a common conclusion determining the negative impact of isolated uses, it might be that, as they coalesce, influence is even more harmful.

Second, all available literature is based on surveys to quantify the amount of time spent on cellphones and GPA to determine academic performance. Even though surveys are a valuable tool, the present study will address the direct impact off cellphone usage by observing *actual time spent* using smart, integrated devices, without relying on student's own perceptions. An experimental method such as the one proposed in the present study is necessary to adjust to inherent biases present on surveys as a metric for understanding the cellphone's influence.

2. Methodology

The literature is typically divided into correlational and experimental studies in both laboratory and real-world classroom settings. Our study employs a mixed strategy, using a hierarchical linear regression (correlational) analysis based on data collected from real-world classrooms, but attempting to control for self-efficacy and academic prowess in order to try to mitigate the issue of correlation/causation.

Our data was collected from three fronts: a survey (on personal information, self-efficacy while learning and usage perception), objective data obtained through the university office (anonymized and with students' permission) on past and current academic performance and data extracted from an App on actual cellphone usage, the latter being the main novel contribution of our paper. All past studies that investigated the implications of cellphone usage in academic performance were based on surveys, questioning each participant about the amount of time they had spent on their cellphones during a given period. However, Duncan et al. (2012) found that, on average, the difference between reported access rate and the actual rate among students might be as high as sevenfold. Thus, to capture the real and indisputable influence of smartphone usage on students' performance, it is necessary to observe their natural behavior during a typical day and collect data that is unrelated to each student's own bias. Therefore, the current experiment was designed to extract information automatically from the student's regular routine, with the least intervention possible from the research team or from the subject of the study.

2.1. Sample

All 250 students (of the 5 different classes) enrolled in 4th semester of the undergraduate course in Business Administration of Fundação Getúlio Vargas (FGV-SP) were invited to participate in an experiment and offered, as a reward for participation, credits equivalent to 10 h of "complementary activities".[2] The 4**th** semester was chosen because FGV students, in their first four semesters at school, are required to complete a series of common mandatory disciplines. After their 5**th** semester, they are allowed to "customize" their curriculum by choosing elective disciplines, which would compromise comparability in our analysis of grades.

[2] Students at FGV must have completed 300 h of complementary activities by the end of the 8th semester in order to graduate.

Invitations took place during class time. The presentation from the experiment's developers to the students took, on average, 10 min and exhaustively explained all the steps of the experiment. However, in order to avoid any bias, the final purpose of the study was not revealed. Students were informed only that the experiment intended to study their cellphone usage habits, but the possible effect on academic performance was not mentioned. The invitation was reinforced by an email to all students, which once again detailed all procedures of the experiment.

Since the experiment involved retrieving sensitive data, ethics clearance was obtained, according to the university's formal procedures, and students were assured in writing that every shared information would be kept anonymous and under no circumstance would be sent to other parties. To ensure secrecy to students, a confidentiality letter was signed by the investigators and the Undergraduate Dean at FGV and delivered to all participating students.

Out of the 250 recruited students, 54 sent their cellphone data to the experiment's investigators, but only 43 of those contained full two-weeks of data, which was the minimum required by the investigators to complete the study. Therefore, the final sample of the experiment was 43 students (N = 43) from 5 different classes, where men accounted for 46.5% and women for 53.5% of the total.

Even though the sample size (N = 43) was statistically significant, it was necessary to investigate the reasons for non-participation in order to check for possible bias or self-selection in our sample. We have tested for differences between our sample of 43 students and the population of 250 students in all objective data available (e.g., gender, age, class, ranking in the entrance exam, average grades, etc.), having found no statistically significant discrepancies. We have also informally surveyed students for reasons for non-participation, to which the main response was that the reward offered (of 10 h of credits of 'complementary activities') was not enticing enough. We have found, therefore, no indication that the sample is biased in any significant way that would compromise our results.

2.2. Independent variables

Participating students were asked to install monitoring applications in their smartphones and let them running for two weeks. By the end of that period, they were asked to export the data and send it through email to the developers of the experiment. Those applications, namely "Moment" for iPhone users and "App Usage Tracker" for Android users, have the one functionality of monitoring how much time one spends using his or her cellphone (usage time is computed only when cellphones are unlocked and thus discarding time spent checking the time or notifications, for instance).

The data received by the investigators contained the total of minutes that each participant spent using his or her smartphone for each day during a two-week period.[3] The average usage time was then calculated by adding total minutes for that period and dividing by 14 (the number of days of the study). Hence, the average usage time per day was calculated in minutes for each student. Results varied from 38.4 min per day (sample minimum) to 396.5 min per day (sample maximum) and the standard deviation (σ) for the sample (N = 43) was 73.4 min per day. The average smartphone usage time of the sample was 230.0 min per day.

Students were also asked to fill a questionnaire with high school average grades and their estimate of how much time they spend on their cellphones on a typical day. Since past studies have suggested that academic performance might be somehow correlated to gender (Peter & Horn, 2005) or to whether a student smoked or not (De Berard, Spielmans, & Julka, 2004; Sánchez-Martínez & Otero, 2009), such personal information was also surveyed.

The questionnaire also contained the validated SE:SRL scale (Zimmerman, Bandura, & Martinez-Pons, 1992), which is an 11-item scale designed to assess student's ability to self-regulate learning related activities, such as delivering homework, participating in class, studying in appropriate distraction-free environments. Students were given a seven-point Likert scale to appoint their perception on how frequent they engaged in each self-regulation activity (i.e., 1 = never to 7 = always). All responses were summed so each student had a score ranging from 11 to 77 where higher scores indicated higher self-efficacy. As previously mentioned, this scale has been shown to be a reliable predictor of academic performance (Pajares, 1996).

Finally, the actual academic performance of each student in the college's entrance exam was obtained through the Undergraduate's Office. This entrance exam (called "*vestibular*") is prepared and applied by FGV and serves as the only criteria for college admission. It comprehends written multiple choice and dissertative questions on subjects learned in high school with considerable level of difficulty, therefore, how well students performed can be considered a solid proxy of how dedicated academically they were in the past and thus a reliable predictor for academic performance in college. The entrance exam performance variable is a straightforward ranking based on the performance of each student on the entrance exam, ranging from 1 for the top performer to approximately 350 for worst performer. In this study's sample, the best performer ranked 4th in the entrance exam and the worst performer ranked 270^{th}.

2.3. Dependent variable

As academic performance allows several interpretations, the official standardized weighted average calculated by FGV (G-MNPS) was used as an objective proxy to assess and compare each student's performance. As published by the Undergraduate's Office of FGV, the G-MNPS score is calculated as follows: for each semiannual subject, students are ranked in an ascending order relatively to their final grade, usually composed by one or two intermediate tests, one academic assignment and one final test. For instance, for a subject with 50 enrolled students, the one with the highest final grade would be ranked number 1 and the worst performer would be ranked

[3] Data was collected from 4/4/2016 to 4/18/2016, halfway through the academic semester.

number 50. Whenever there are two equal grades, every student with the same grade receives the same higher ranking. In the hypothetical class of the example above, if there were 5 students with a final grade equal to 10 (i.e., the maximum grade) and one with the final grade equal to 9.5, all of the first five would be ranked number 1 while the student with the 9.5 final grade would be ranked number 6.

The standardized average is computed dividing the attributed ranking by the total number of enrolled students in each subject. Following the example above, a student ranked 30 in that class, would have a standardized average of 0.6 (30 divided by 50). Finally, the weighted standardized average is calculated using credit hours of each subject (ranges from 2 to 6 h in mandatory subjects) as weight. The final average is given in percentage points. Since it is more intuitive for the better performing students to have the higher average, the published G-MNPS is the subtraction of the calculated weighted average (as shown above) from 100%. For instance, if the hypothetical student above was enrolled in that subject only, his or her final G-MNPS would be 40% (100% minus 60%). Therefore, values of the dependent variable in the sample used for the present study could range from 0 to nearly 98.4 (since most subjects have 60 enrolled students at most). From the study's sample, the minimum G-MNPS observed was 24.1 and the maximum was 91.8. The sample's standard deviation (σ) was 17.9.

As participating students were enrolled in 4th semester of the Business Administration course, the study used the accumulated G-MNPS from the first to the third semester as dependent variable. Since students at FGV are only allowed to enroll in non-mandatory (elective) subjects from the 5th semester onwards, the accumulated G-MNPS used is comparable between students, given that all went through the same disciplines, tests and activities, and thus, higher scores mean better academic performance. The investigators obtained the participants' information through the Office of Undergraduate Courses of FGV.

3. Data analysis

All analyses were made using Minitab Statistical Software for Windows (version 17, State College, Pennsylvania). First, in order to find significant differences between the average G-MNPS of subgroups of the sample, independent t-tests and ANOVA analyses were performed. Subgroups of men versus women, smokers versus non-smokers, as well as subgroups of different classes (the sample contained students from five different classes) were analyzed. Second, Pearson's correlation was calculated between the independent variables in order to illustrate the relationship between them. The previously mentioned variables were considered: G-MNPS, SE:SRL, entrance exam performance and cellphone usage.

A hierarchical regression was performed next to verify if there is any statistically significant relationship between cellphone usage and academic performance. This method grants an easy observation of whether the addition of a new variable (cellphone usage) to a regression model which already contains well-known predictors (gender, SE:SRL and entrance exam performance) results in a more precise model with a higher R^2 but still significant p-value (below 5%). Therefore, if the addition of the cellphone usage variable increases the R^2 of the regression model, it would be possible to assert the relationship of this variable to the independent variable (G-MNPS) and the coefficient (β) of that variable would indicate the extent of its impact.

Finally, the sample was divided in two subgroups relatively to the average cellphone usage time per day of each student. Students with an average usage time higher than 300 min per day were considered "heavy users" and the ones with an average usage time lower than 300 min per day were labeled "light users". Heavy users accounted for 35 students and the average G-MNPS of that cluster was 45.4 ($\sigma = 16.9$) while the remaining 8 were light users and had an average G-MNPS of 59.5 ($\sigma = 17.3$). An ANOVA analysis was conducted to determine if there was any statistical significance in the difference between the average G-MNPS between the two clusters.

4. Results

4.1. Descriptive statistics

Assuming outliers as observations above or below three standard deviations from the sample's mean (Rosen et al., 2013), none of the observations of the experiment's sample should be removed, once the minimum value of the initial sample was 38.4 min per day and the maximum was 396.5 min per day, while outliers would be observations above 450.2 or below 9.8. Thus, the final sample size of the study is 43. The average cellphone usage time of the sample was 230.0 min per day with a standard deviation of 73.4 min per day. As for G-MNPS, the sample averaged 56.8 and the standard deviation was 17.9. Table 1 provides a summary of the descriptive statistics for all variables.

Table 1
Descriptive statistics.

	Minimum	Maximum	Average	Standard Deviation
G-MNPS	24.1	91.8	56.8	17.9
SE:SRL	3.0	5.0	4.7	0.8
Entrance Exam	4.0	270.0	133.2	76.6
Cellphone Use	38.4	396.5	230.0	73.4

Note. G-MNPS = standardized cumulative weighted average; SE:SRL = self-efficacy for self-regulated learning.

Table 2
Demographic information.

	Students	% Sample	Average usage (min/day)	G-MNPS
Men	20	46.5%	217.7	54.8
Women	23	53.5%	240.7	58.6
Class 1	12	27.91%	242.9	60.1
Class 2	10	23.26%	215.0	62.2
Class 3	1	2.33%	176.0	59.2
Class 4	10	23.26%	209.2	55.1
Class 5	10	23.26%	255.7	58.1

Note. G-MNPS = standardized cumulative weighted average.

The sample was evenly distributed among men and women as well as between classes. Men comprised 46.5% of the total sample of 43 students while women represented 53.5%. The sample of 20 men spent on average 217.7 min per day using their cellphones and had an average G-MNPS of 54.8, while women spent on average 240.7 min per day and had an average G-MNPS of 58.6. Meanwhile, classes 1 to 5 sampled 12, 10, 1, 10 and 10 students, respectively (see Table 2).

Independent sample t-tests were performed and showed no significant difference in the average G-MNPS between males and females (p-value = 51.3%). Likewise, an ANOVA test showed no significant difference in the average G-MNPS between all 5 classes (p-value = 38.7%) and therefore, both of these variables (gender and class) were excluded from further analyses. Moreover, none of the participants declared to be smokers and, as such, no comparison could be made between smokers and nonsmokers.

Table 3 summarizes the correlation coefficients between the resulting variables, and their interpretation ensures their consistency as predictors of academic performance. As expected, there was a positive and high correlation between G-MNPS and the self-efficacy measure (SE:SRL). That same measure has a negative and high correlation with the entrance exam because of the inverted scale of the latter variable (better students have lower rankings), which is the same reason for a negative correlation between the entrance exam and G-MNPS. Moreover, cellphone usage was negatively correlated both with G-MNPS and SE:SRL. All correlation coefficients were statistically significant (p-value $< 5\%$).

4.2. Hierarchical regression

In order to conclusively answer the central question of this study, which is to state the extent of the impact, if any, of cellphone usage in academic performance, a hierarchical regression analysis was conducted, by progressively adding the variables that were shown to be statistically significant in the previous descriptive analysis. If adding the cellphone usage variable to a regression model already composed of other significant and predicting variables makes the output even more precise (higher R^2), it would be safe to claim that there is indeed a relationship between that explanatory variable and the dependent variable (G-MNPS, as a proxy for academic performance).

As shown in Table 4, each variable added to the model contributed to a more precise prediction of the dependent variable with statistical significance (p-value $< 5\%$). The first regression model was composed only by the SE:SRL variable as predictor of G-MNPS. As previously mentioned, SE:SRL has been found, in previous studies, to be a solid predictor in a variety of settings, including academic, since it assesses an individual's capacity to proactively organize and schedule the activities necessary to a more efficient content absorption, which likely results in better academic performance, regardless of the measure considered.

The R^2 of this first model was 30.4%, illustrating the significant (p-value < 0.00) and positive ($\beta = 10.89$) relationship between the variables. Sequentially, the entrance exam variable was added and a significant (p-value < 0.026) negative relationship ($\beta = -0.065$) was revealed. It is important to note, however, that the negative coefficient is a result of the computation method for the entrance exam variable. The best performing student is ranked 1 while subsequent worse students will receive higher rankings. Therefore, the lower the entrance exam ranking, the better the student performed and the higher is his or her G-MNPS. Finally, the cellphone usage variable was added to the regression model and the output was a significant (p-value < 0.04) negative relationship with G-MNPS ($\beta = -0.063$). The analysis of the final regression model shows that 43.6% of the sample's variance is explained by the three independent variables mentioned above ($R^2 = 43.6\%$), including the observed average cellphone usage time per day.

Table 3
Pearson correlation coefficient.

	G-MNPS	SE:SRL	Entrance Exam	Cellphone Use
G-MNPS	–			
SE:SRL	0.816	–		
Entrance Exam	−0.319	−0.522	–	
Cellphone Use	−0.301	−0.636	−0.067	–

Note. G-MNPS = standardized cumulative weighted average; SE:SRL = self-efficacy for self-regulated learning. Entrance Exam has inverted scale (better students have lower rankings).

Table 4
Hierarchical regression outputs.

	SE:SRL	Entrance Exam	Smartphone Usage
R^2	30.4%	37.1%	43.6%
ΔR^2	–	+6.7pp	+6.5pp
Regression p-value	0.00	0.00	0.00
Variable p-value	0.00	0.026	0.040
Regression Coefficient (β)	10.2	−0.065	−0.063

Note. G-MNPS = standardized cumulative weighted average; SE:SRL = self-efficacy for self-regulated learning; Entrance Exam has inverted scale (better students have lower rankings).

Therefore, the regression equation that explains 43.6% of the variance of the academic performance, measured as the cumulative standardized weighted average of 43 sampled students, considering the exposed independent variables, would be the following:

$$\boldsymbol{G-MNPS} = 34.7 + 10.2\,\boldsymbol{SE}:\boldsymbol{SRL} - 0.065\,\textbf{\textit{Entrance Exam Rank}} - 0.063\,\textbf{\textit{Average Cellphone Usage Time per Day}}$$

The regression's equation reveals the magnitude of the smartphone's use impact. Each 100 min spent using these devices on average per day corresponds to a reduction in a student's G-MNPS of 6.3 points, in a range from 0 to nearly 100. The extent of this effect is alarming. First, it is equivalent to a decline of astounding 96.4 positions at the entrance exam's ranking (ranging from 1 to 350), which comprehends the performance on a long and thorough test, assessing a series of specific knowledges. Second, it is a variable fully under control of each student, which suggests that a more disciplined behavior might be enough to bring very positive results, since the G-MNPS is the criteria of prioritization for the enrollment in a range of courses at FGV, as well as for acceptance in exchange programs abroad.

A final ANOVA test was performed to compare the average G-MNPS of the heavy users' subgroup with the average of the light users' subgroup, as previously described. A significant difference between the average of the subgroups was found ($p\text{-value} < 0.043$). As illustrated by the chart below, the heavy users G-MNPS average is only 76.2% of the light user's average (see Charts 1–3).

4.3. Usage during class time vs during free time

One interesting refinement of our study is to investigate whether usage during a specific time of the day (e.g., during class as opposed to during free time in weekdays or weekends) is particularly harmful. We were able to test this for the 43 students of our sample who used iPhones, since the App “Moment” registers the exact hour and minute of usage each day. Given that students at FGV typically have classes from Monday to Friday from 7:00AM until 4:40PM, with predetermined break periods, we were able to filter usage to consider only periods of the day when students were supposed to be attending to class and re-run our regressions accordingly. Chart 4 below shows average usage per student during workdays (Monday through Friday), breaking the data up to reflect usage during class time, non-class time spent at school (e.g., breaks) and ‘free time’, i.e., time outside school (before 7:00AM and after 4:40PM).

First, we re-ran the original regression to include only students with iPhones. Since they represented the vast majority of all students in our original sample, results were practically identical to the previous model. The R^2 of this first model was unaltered at 43.6%. Cell phone usage during weekdays had a significant ($p\text{-value} < 0.040$) and negative relationship ($\beta = -0.064$) with academic performance (for better comparison, we have excluded weekends from the data) (see Table 5):

We then conducted a similar regression including only usage **during class time**. Table 6 shows the result of the new regression considering only usage during class time:

With this refinement, R^2 increased slightly to 44.0% while the coefficient of cellphone usage *during class time* was twice as high as before ($\beta = -0.120$; $p\text{-value} < 0.033$ vs. $\beta = -0.063$; $p\text{-value} < 0.040$ before). The new regression equation would be the following:

$$\begin{aligned}\boldsymbol{G-MNPS} = {}& 34.8 + 9.39\,\boldsymbol{SE}:\boldsymbol{SRL} - 0.064\,\textbf{\textit{Entrance Exam Rank}}\\ &- 0.120\,\textbf{\textit{Average Smartphone Usage per Day During Class}}\end{aligned}$$

Therefore, each 10 min spent per day using smartphones *during class* corresponded to a reducion in a student's G-MNPS by 1.20 points (in a range from 0 to nearly 100). To put this result in perspective, a student would have to rank almost 19 positions lower at the entrance exam (in a ranking from 1 to 350), *ceteris paribus*, for the same type of effect to be observed. The magnitude of the impact is impressive, especially since the other variables considered are much broader in nature: the entrance exam, for example, consists of a thorough test on all major academic subjects for which students prepare along their whole school lives.

In the graphs below we have plotted the relationship between academic performance and smartphone usage in three different periods: during class time (Chart 5), during weekends (Chart 6) and during weekdays’ free (i.e., non-class) time (Chart 7). Since the scales of the graphs are the same, it becomes immediately visible, by comparing the slopes of the tendency lines, that usage during class time correlated more significantly with performance than usage during weekends, for example.

The higher correlation might be due to the fact that limiting measurement to “class time” generates a more precise proxy of the potentially distracting uses we intend to analyze, since the broader “average daily usage” would include other non-dispersive uses

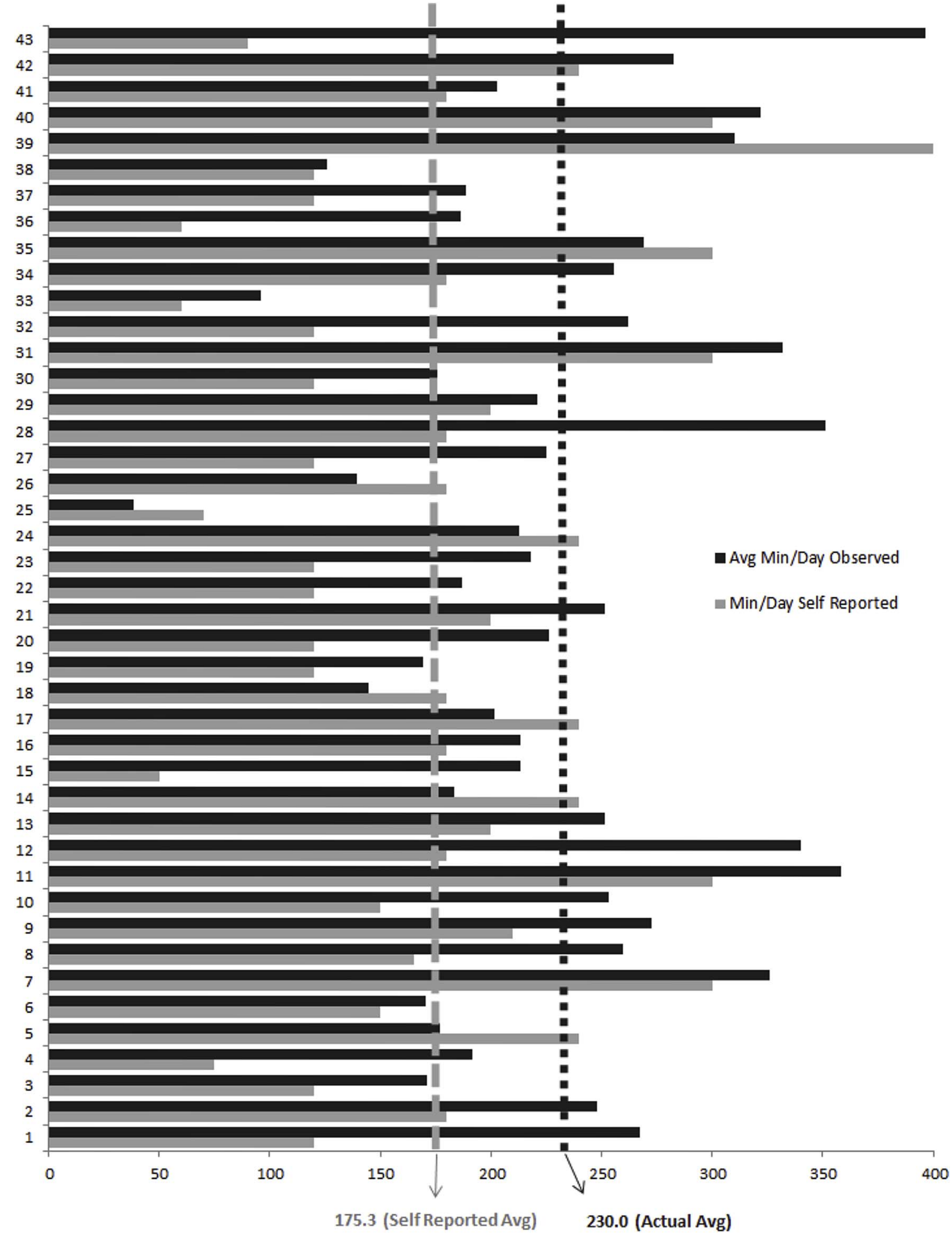

Chart 1. Smartphone Usage – Actual vs Reported.
Source: Students' reports; compiled by authors

like, for example, geolocation Apps like Waze or Google Maps while driving.

Nonetheless, the magnitude of the difference between the scenarios gives further support to the hypothesis that students might be getting distracted by technology during class time and loosing focus on lectures and other academic activities. Thornton, Faires, Robbins, and Rollins (2014), for example, report that the mere presence of an unused cell phone may be sufficiently distracting to

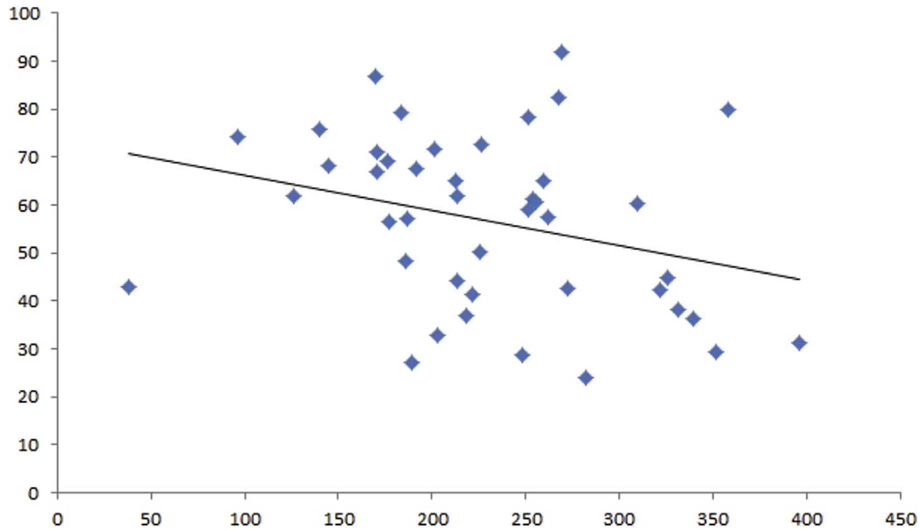

Chart 2. Average Usage/Day vs Position in Ranking.
Source: FGV and students' reports; compiled by authors

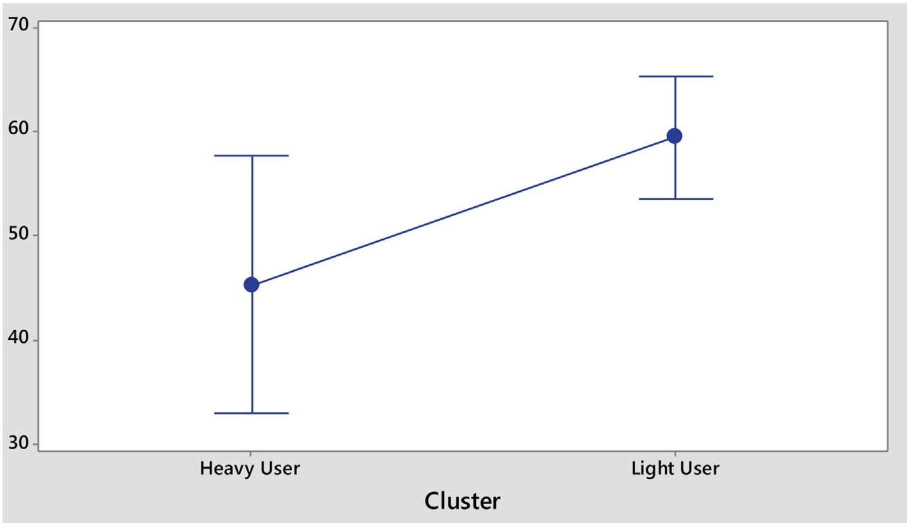

Chart 3. Average G-MNPS distribution by cluster.
Source: FGV and student's reports; compiled by authors

produce diminished attention and deficits in task-performance. Such an effect might as well be occurring in classrooms, as the need to be incessantly connected to social media platforms and mobile messaging Apps competes with lectures for students' cognitive resources.

5. Conclusion

The central question of this study was whether increasing smartphone usage among college students has a significant impact on their academic performance. As both the independent and dependent variables for this question could be subjectively interpreted, objective measurable proxies were collected from a sample of 43 students enrolled in the 4th semester of the Business Administration Undergraduate course of FGV, a Brazilian business school. To assess academic performance, the cumulative standardized weighted average (G-MNPS) was obtained with the Undergraduate's Office while actual cellphone usage data was collected through monitoring applications (namely, "Moment" and "App Usage Tracker") voluntarily installed by participating students.

Other independent variables were used as known predictors in this study's initial analysis since previous research had already proven their significant relationship with academic performance. Peter and Horn (2005) found in a sample of students that females had higher GPAs compared to males while another study suggested that smokers performed worse than nonsmokers (De Berard et al., 2004; Sánchez-Martínez & Otero, 2009). However, in this study's sample, a *t*-test revealed no significant difference in G-MNPS

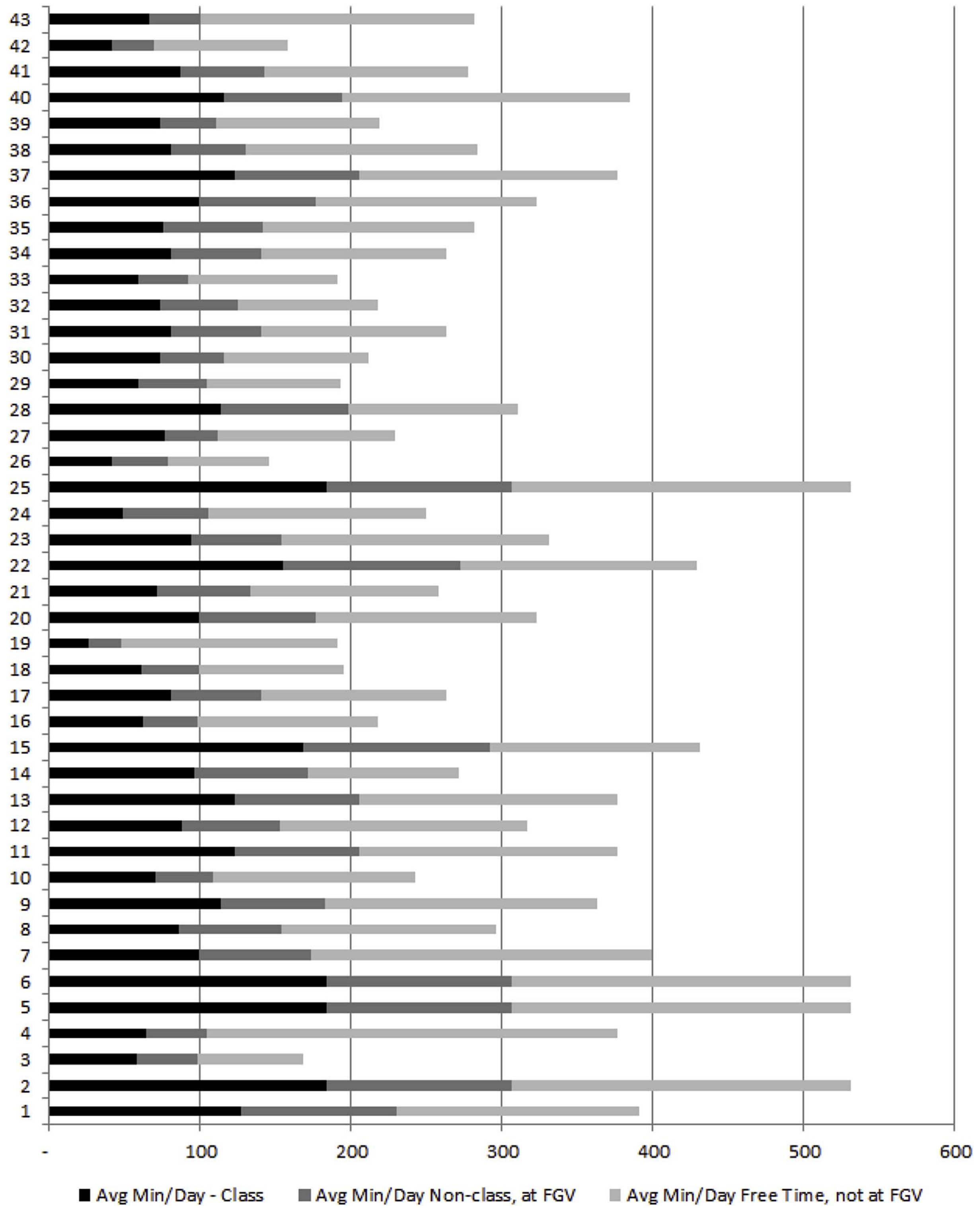

Chart 4. Breakdown of average smartphone usage during weekdays.
Source: FGV and students' reports; compiled by authors

between genders. Furthermore, none of the participating students declared to be smokers. Therefore, those two variables were excluded from further analysis.

After initial statistical analysis and assumption checking for outliers, normality and homoscedasticity, a hierarchical regression

Table 5
Usage during weekdays: Regression outputs.

	Coefficients	St Error	t-stat	P-value
Intercept	34,727	15,194	2286	0,028
SE:SRL	10,164	2551	3985	0,000
Entrance Exam	−0,066	0028	−2308	0,026
Smartphone Usage (**weekday**)	−0,063	0030	−2130	0,040

SE:SRL = self-efficacy for self-regulated learning; Entrance Exam has inverted scale (better students have lower rankings).

Table 6
Usage during class time: Results.

	Coefficients	St Error	t-stat	P-value
Intercept	34.838	15.020	2.319	0.026
SE:SRL	9.389	2.609	3.599	0.001
Entrance Exam	−0.064	0.028	−2.265	0.029
Smartphone Usage (**class time**)	−0.120	0.054	−2.204	0.033

SE:SRL = self-efficacy for self-regulated learning; Entrance Exam has inverted scale (better students have lower rankings).

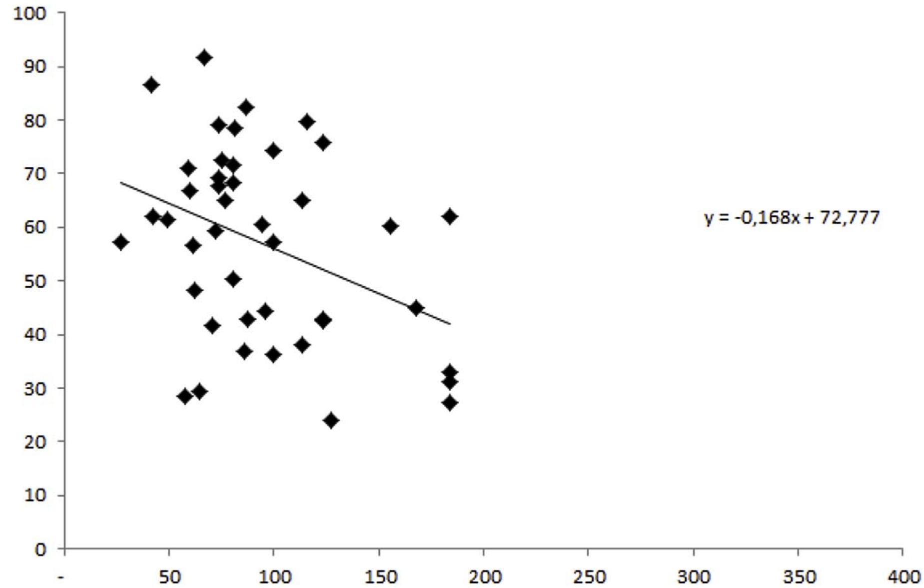

Chart 5. Average Usage/Day during Class time x Position in Ranking.
Source: FGV and students' reports; compiled by authors

was performed with the remaining explanatory variables. The entrance exam performance and the SE:SRL scale were used as known predictors. The output of the regression model with those two variables only, showed a significant relationship between them and G-MNPS. In that model, 37.1% of G-MNPS's variance was explained by the independent variables. Finally, when smartphone usage variable was added, the regression model revealed a negative significant relationship between the average time spent using cellphone and G-MNPS, while increasing the percentage of the dependent variable's explained by the model to 43.6%. Therefore, this study suggests, based on actual smartphone usage data and official grade average records, that it is more likely that a student who uses less his or her cellphone will have a higher G-MNPS than the one who uses more, given an equal performance in the college's entrance exam and same belief to self-regulate their own studying settings.

The extent of the negative relationship between smartphone's usage and academic performance found in this study is compelling. Every additional 10 min spent (on average per day) using a cellphone device is related to a reduction in that student's G-MNPS by 0.63 points (on a scale from 1 to 100).

The magnitude of this effect is even higher if we consider only smartphone usage *during class time*: R^2 increases to 44.0%, while β almost doubles to −0.120 (p-value < 0.033) from previous −0.063 (p-value = 0.040), when considering full day average usage. Therefore, each 10 min spent per day using cellphones *during class* corresponds to a reduction in a student's G-MNPS by 1.2 points. This effect is similar, in magnitude, to a decline of almost 19 positions at the entrance exam ranking (ranging from 1 to 350).

The scale of the smartphone's impact found is alarming: 100 min of additional cell phone usage per day would be enough, for

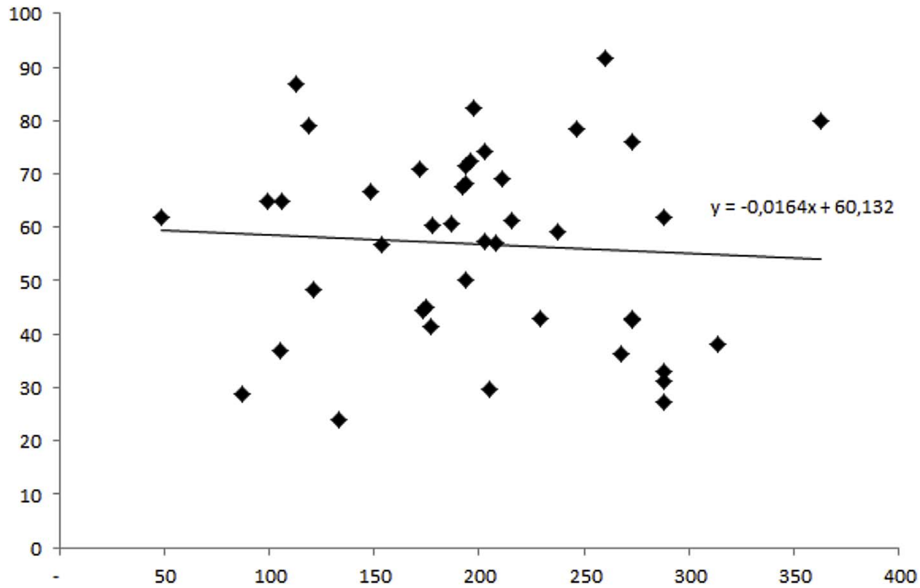

Chart 6. Average Usage/Day during Weekends x Position in Ranking.
Source: FGV and students' reports; compiled by authors

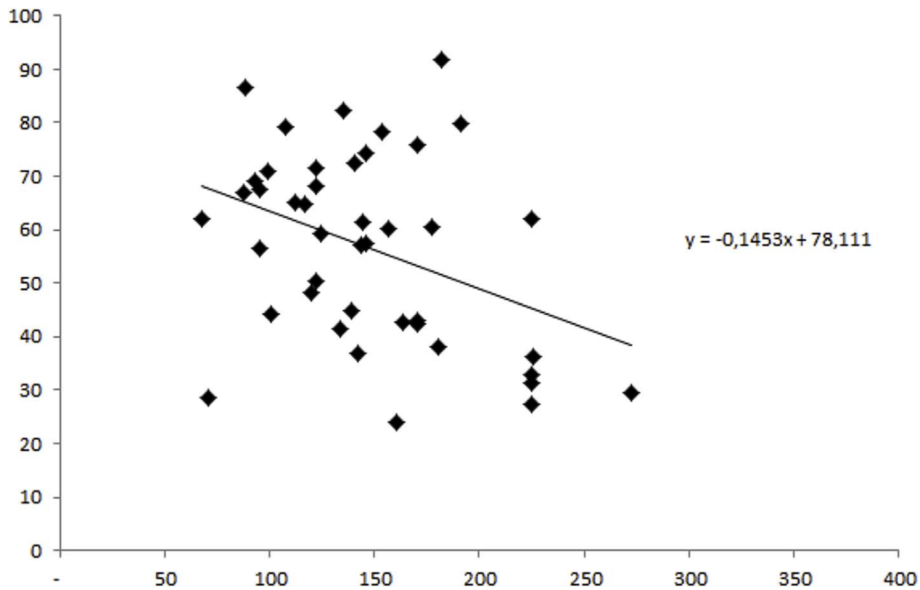

Chart 7. Average Usage/Day during Working Days' Free Time x Position in Ranking.
Source: FGV and students' reports; compiled by authors

instance, to exclude a top performing student from the Honor's Board of FGV, since the difference of the first mentioned student's G-MNPS to the last is usually 9 to 13 points. Moreover, students might spoil further experiences, since the G-MNPS is applied at FGV as the criteria for choosing students to be accepted in exchange programs abroad and for future non-mandatory courses at FGV.

This conclusion endorses previous research that investigated the impact of particular uses of cellphone, social medias and gaming on academic performance, notably Jacobsen and Forste (2011), who showed the negative impact of texting and calling, Jackson et al. (2011) who associated heavy gaming with lower GPAs and Lepp et al. (2015) who studied the cellphone as an integrated platform with a negative relationship with GPA. Therefore, it offers further support to the hypothesis that, despite the set of learning-efficient tools available in current smartphones, these devices are more often a source of distraction in classrooms and any other setting dedicated to studying, rather than a productive platform to find and share information, exercise new learnings and interact with students or professors.

The negative influence of cellphone usage in academic performance also reinforces the findings of Ophir et al. (2009) which concluded that young students often overestimate their ability to multitask. The user's belief that he or she can efficiently pay attention to other activities such as absorb content from a lecture, complete homework or study while keeping the cellphone on standby and using it from time to time could be misleading, as students are more often tempted to game, check social medias and connect with colleagues. However, current smartphones can still be a very powerful tool that should be used to contribute to learning. Therefore, it is possible that its application brings productive results in specific academic settings while jeopardizes student's performance in others. Accordingly, further research is needed to investigate these specific settings and to better understand how to effectively regulate cellphone use.

Furthermore, two other concerns should be explored to extend the understanding of the cellphone's and other technology's impact on academic performance. First, the indirect impact provoked by student's overuse. For instance, professors might be distracted by extensive use of cellphones, computers and tablets, which could potentially jeopardize the quality and clarity of lectures or other class activities. Likewise, heavy users might distract other students by urging them to check an application, send or answer a message or interact in any other way. Second, it might be that some specific uses of cellphone are more harmful than others. In fact, previous research showed that some uses can be positively related to academic performance. Chen and Tzeng (2010) associated extensive use of Internet for gaming with lower academic performance but also showed that students who sought more for information in the Internet overperformed academically compared to the ones who searched less. Hence, further research should make it clear which particular uses of cellphone should be incentivized when seeking better academic performance.

This study was based in extensive previous research in the field and used consistent metrics to answer its central research question. However, discretion is advised for any generalization given two main limitations. First, all participants in the experiment were from the same college, same course and same semester. Second, the experiment's sample is significant, but small, and thus fails to comprehend a wider range of diversity as well as to be more representative of the college's universe. Finally, the period of analysis (i.e., 14 days of data) is relatively short.

Despite its limitations, this study coalesces to previous research and brings more data that motivates further exploration in the field. It is indisputable that smartphones will keep developing in a distinguished pace along with possible new disruptive technologies that may be introduced, forcing educators and other stakeholders to have a clear, definitive answer to which are the conditions and settings where cellphone applications can indeed contribute to learning and the ones in which educational tools will be undermined by the temptation of leisure activities.

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