Smartphone Use and Academic Performance: Correlation or Causal Relationship?

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Abstract

After a decade of correlational research, this study is the first to measure the causal impact of (general) smartphone use on educational performance. To this end, we merge survey data on general smartphone use, exogenous predictors of this use, and other drivers of academic success with the exam scores of first-year students at two Belgian universities. The resulting data are analysed with instrumental variable estimation techniques. A one-standard-deviation increase in daily smartphone use yields a decrease in average exam scores of about one point (out of 20). When relying on ordinary least squares estimations, the magnitude of this effect is substantially underestimated.

Keywords: smartphone use; academic performance; causality.

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1. Introduction

Across OECD countries, in recent years, the question of whether or not smartphone use (i.e. the time that an individual is active on her/his smartphone per day or per week) affects performance and quality of life has occupied an important place in social debate (see, e.g., Eliahu, 2014; OECD, 2017; Samuel, 2017). This debate is fuelled by a multidisciplinary scientific literature that not only relates smartphone use to reduced performance during driving, walking, and working, but also to poorer study results (Abouk and Adams, 2013; Andreassen, 2015; Bhargava and Pathania, 2013; Lepp et al., 2013; Levine et al., 2012). Scholars' interest in the connection between smartphone use and the latter outcome (poorer study results) is not surprising. Smartphone use in the OECD region has increased massively during the past decade (Lepp et al., 2015; Vanhaelewyn and De Marez, 2017), such that its potential adverse effect on educational performance may have a major societal impact. In the present study, we contribute to this literature concerning the interplay between (general) smartphone use and educational performance.

There are several theoretical mechanisms that support a causal effect of smartphone use on educational performance. On the one hand, the use of a smartphone may improve the efficiency of students' study activities by allowing them to continuously search for (study-related) information and by facilitating teamwork (Chen and Yan, 2016; Hawi and Samaha, 2016; Hwang et al., 2014). On the other hand, research has shown that students see their smartphones primarily as sources of entertainment, rather than as study tools (Barkley and Lepp, 2013; Lepp et al., 2013). As a result, a trade-off, in terms of time use à la Becker (1965) between smartphone use and study activities can be expected (Chen and Yan, 2016; Lepp et al., 2015). Apart from this trade-off in time use, there are two other theoretical reasons why a negative relationship could be expected. Firstly, the desire to use one's smartphone in order to not miss anything that is happening online—nowadays often referred to as 'FOMO' (fear of missing out)—and to continuously interact with the rest of the world may lead to a lack of the kind of focus necessary to achieve good study performance (Chen and Yan, 2016; Elhai et al., 2016; Firat, 2013). Secondly, the constant switching back and forth between study-related and social activities on the smartphone could result in cognitive overload and inefficiency (Chen and Yan, 2016; Compernolle, 2014;

Junco, 2012; Oulasvirta et al., 2012).

The recent empirical literature on this phenomenon is in line with the dominance of mechanisms that predict a negative relationship between smartphone use and educational performance. We are aware of seven studies that directly investigated their empirical association: Chen and Ji (2015), Lepp et al. (2014), Lepp et al. (2015), Li et al. (2015), Ng et al. (2017), Olufadi (2015), and Wentworth and Middleton (2014). More specifically, analysing survey data from the United States, Lepp et al. (2014, 2015) and Li et al. (2015) found a negative association between total smartphone use and the actual or self-reported grade point average (GPA) of college students, while Wentworth and Middleton (2014) concluded that there was no such association in their data. In addition, Ng et al. (2017) and Olufadi (2015) determined a negative association between mobile phone use during tertiary education and GPA in Malaysia and Nigeria, respectively. Finally, Chen and Ji (2015) reported that university students in Taiwan who used their personal electronic device(s) more for non-educational pursuits, had a lower first-year GPA. We refer to Amez et al. (2018) for a thorough review of this literature.[1]

As several of these studies themselves indicated, however, no causal interpretation can be given to any of their results. This is due to an endogeneity problem. The studies' results were obtained through correlation analyses and/or (multiple) linear or logistic regression analyses based on cross-sectional data. As a consequence, the measured non-positive association between smartphone use and academic performance might reflect variation in unobserved personal characteristics, such as intelligence, general ability, and motivation, which these studies did not control for, but which could affect both smartphone use and academic performance. This is an important limitation. As long as there is uncertainty as to whether the negative association between smartphone use and educational performance

[1] In addition, a few other articles relate smartphone addiction (instead of general use) to educational underperformance (Hawi and Samaha, 2016; Samaha and Hawi, 2016). Besides this literature on the association between general smartphone use (and addiction) and educational performance, a further few articles exist that examine the association between the use of specific electronic applications (via one's smartphone and/or other devices) and study performance. For example, previous research investigated the association between study performance and the extent to which people call (Hong et al., 2012; Jacobsen and Forste, 2011) and check Facebook (Kirschner and Karpinski, 2010; Lee, 2014). However, these studies ignore the fact that the use of electronic devices for a particular application is strongly correlated with their use for other activities (Chen and Yan, 2016; Lepp et al., 2015), potentially resulting in an omitted variable bias. Finally, work has been done on the effectiveness of smartphone ban interventions in classrooms (Beland and Murphy, 2015).

reflects a causal relationship (and not merely a connection via confounding factors), there is no solid basis for interventions such as the smartphone ban in French schools (Samuel, 2017).

This study is the first to attempt to measure the causal impact of (overall) smartphone use on educational performance. To this end, we exploit data from 696 first-year students at two Belgian universities, who were surveyed in December 2016 using multiple scales on smartphone use as well as predictors of this smartphone use and a battery of questions concerning (potential) other drivers of success at university. This information is merged with the students' scores on their first exams, taken in January 2017. We analyse the merged data by means of instrumental variable estimation techniques. More concretely, to be able to correctly identify the influence of smartphone use on academic achievement, in a first stage, the respondents' smartphone use is predicted by diverging sets of variables that are highly significantly associated with smartphone use, but not directly associated with educational performance. In a second stage, the exam scores are regressed on this exogenous prediction of smartphone use and the largest set of control variables used in the literature to date.

The remainder of this article is structured as follows. In Section 2, we inform the reader about the data gathered to meet our research goals and about our approach to the making of causal inferences based on these data. Then, in Section 3, we discuss the findings of our main analyses and some robustness checks. The final section states our conclusions, with a preview for potential further research.

2. Methods

2.1 Research Population

The data used to investigate the effect of smartphone use on academic performance comes from merging unique survey data from first-year university students in Belgium with their first university exam scores. Our survey took place at the end of their first semester, in December 2016, i.e. just before the start of the Christmas holidays. These holidays are used by students to prepare for their first semester exams, which take place immediately after the Christmas holidays. More concretely, we surveyed all students attending the last lecture of a first-semester course in all 11 Bachelor programs in three faculties at Ghent University and University of Antwerp, i.e. the two main universities in the two biggest cities in Flanders, namely Ghent and Antwerp. These programs were: Business and Economics, Commercial Sciences, and Public Administration and Management in the faculty of Economics and Business Administration at Ghent University; Business Economics, Economic Policy, Business Engineering, and Management Information Systems in the faculty of Applied Economics at University of Antwerp; and Communication Studies, Political Science, Social and Economic Sciences, and Sociology in the faculty of Social Sciences at University of Antwerp.

In total, 1117 students attended the classes at the start of which we gathered our survey data. This was done by means of a paper-and-pencil questionnaire. Among these students, 767 indicated, as a part of the survey, that they were in their first year at university (the other ones had had to resit the course, or were taking it as an elective course in the context of another program). We retained only this homogeneous group of first-year students. At the end of the survey, the attending students were asked whether they consented to their answers being merged with their first-semester exam scores by a third party, and 747 of the 767 first-year students consented. For 17 of them, no exam scores were observed, as they had dropped their courses by the end of the exam period. Finally, we had to exclude 18 students who indicated that they did not have smartphones, and 16 students with missing or inconsistent information. Consequently, our analyses are based on a sample of 696 first-year students with complete information.

2.2 Data

We surveyed smartphone use by means of three indicators. Firstly, we let the participants fill in the Smartphone Usage Subscale of Rosen et al. (2013). This scale comprises nine items in which respondents indicate the frequency with which they use their smartphone for nine activities (such as ‘making and receiving mobile phone calls’ and ‘checking for text messages’), rated on a 10-point frequency scale (ranging from ‘never’ to ‘all the time’). These items were averaged to derive a scale from 1 to 10, with higher scores indicating more frequent smartphone use. The Cronbach’s alpha on this scale for our sample was 0.746. In the remainder of the present manuscript, we refer to this scale as ‘overall smartphone use’. In addition, by analogy with Rosen et al. (2016), we surveyed the participants on their smartphone use during classes and during study activities by means of the items: ‘During a typical class period, how often do you check your smartphone for something other than the time?’ and ‘During a typical hour of studying, how often do you check your smartphone for something other than the time?’. These had to be scored on a 7-point frequency scale (ranging from ‘never’ to ‘more than eight times’; Rosen et al., 2016). In the remainder of this manuscript, we refer to these scores as ‘smartphone use while attending class’ and ‘smartphone use while studying’. Panel A of Table 1 presents the average scores for the three indicators of smartphone use in our sample. The average score with respect to overall smartphone use is 5.701, while the average score with respect to smartphone use while attending class and while studying is 4.499 (i.e. between three and five times per course period) and 3.198 (i.e. close to two times per hour of study), respectively.

<Table 1 about here>

Next, we gathered information on variables that were important for our statistical analysis being predictors of smartphone use that were assumed to have no independent impact on exam scores. These potential instruments—the adequacy of diverging sets of which are tested in Section 3—are: (i) whether the respondent had 4G technology on their smartphone (binary variable); (ii) six binary variables capturing the respondents’ smartphone contracts (i.e. whether the monthly download volume included in the contract was 1GB or more, as well as indicators of having Proximus, Base, Orange, Telenet, or another player as an operator); (iii) perceived quality of the WiFi network in the respondents’ classrooms (based on the respondents’ answers to the item ‘How do you evaluate the average quality of your internet access in the classrooms this semester?’, ranging from 1 (very bad) to 5 (very good)); and (iv) whether the respondent had to pay their smartphone costs themselves (binary variable). Panel B of Table 1 shows the respondents’ average scores on these instruments, for the full sample as well as for the subsamples of individuals with a below-average versus above-average score on the overall smartphone use scale. The indicators of 4G technology and a substantial download volume show the highest correlations with smartphone use.

With respect to (additional) control variables for our analyses, firstly, we constructed indicator variables of the programs in which the data were gathered. In addition, we surveyed the respondents on the socioeconomic determinants of exam scores proposed in Baert et al. (2015): gender, age, (foreign) origin, language spoken at parental home, paternal education—we also surveyed maternal education, but this turned out to be heavily correlated with paternal education, so that we did not retain this construct for our analyses—household composition, relationship status, general health, living in a student room (versus at home), distance between home and university, and prior educational attainment. In addition, we let the respondents fill in the 28 items of the College Version of the Academic Motivation Scale of Vallerand et al. (1992), yielding a motivation score between 1 and 7, and the six items of the Webexec scale of Buchanan et al. (2010), yielding a measure of executive functioning problems between 1 and 5. A final control variable captured by our survey was whether or not the respondents used their laptop (versus paper and pencil) to take notes during classes most of the time. As shown in Panel C of Table 1, the subsample of individuals with a relatively high smartphone use particularly comprises more students (i) in the Political Science program, (ii) with a migration background, (iii) in (fairly) bad health, (iv) using their laptop to take notes in class, (v) living close to university, and (vi) having graduated from secondary education with low marks. As these factors are also likely to affect academic performance, controlling for them is desirable when identifying the impact of smartphone use on exam scores.

Finally, Panel D of Table 1 presents statistics on the three academic outcome variables we constructed based on the respondents' exam scores for their first semester at university. Our main outcome variable ('average score: completed exams') is the average of the respondents' scores (graded between 0 and 20) over all exams sat by them, leaving out observations for which they were not present at the exam. A first alternative outcome variable ('average score: potential exams') equals our main outcome variable except that the exam score for when students did not show up is recoded as the minimum score of 0. A second alternative outcome variable ('fraction of exams passed') is calculated by dividing the number of exams the respondents passed (by obtaining at least 10 out of 20 points) by their total number of exams taken.[2] In line with the correlational literature cited in Section 1, all academic performance indicators are substantially less beneficial in the subsample of

[2] Analyses at the individual exam score level (with course fixed effects) yielded very similar research conclusions.

respondents with relatively high smartphone use. However, this comparison does not take into account selection, neither on the observable respondent characteristics listed in Panel C of Table 1, nor on the unobservable characteristics that may correlate with both smartphone use and academic performance. The instrumental variable regression approach we discuss in the following subsection deals with this double endogeneity problem.

2.3 Empirical Approach

Our main strategy for tackling the endogeneity of smartphone use (as captured by one of the variables in Panel A of Table 1) and academic performance (as captured by one of the variables in Panel D of Table 1) is to rely on an instrumental variable regression framework (Angrist and Pischke, 2008; Baert et al., 2015). In the first stage of this two-stage least squares (2SLS) approach, the respondents' smartphone use is predicted by (a selection of) the instrumental variables included in Panel B of Table 1. As these variables are assumed to affect educational performance (after controlling for the other drivers of success at university included in Panel C of Table 1)[3] only indirectly through actual smartphone use, this first stage yields an 'exogenous prediction' of the respondents' smartphone use. In the second stage, academic performance is regressed on this predicted use (and the control variables).

Both assumptions on which the causal interpretation of our results is based are tested empirically. Firstly, with respect to the strength of our instrumental variables (i.e. their predictive power concerning smartphone use), we conduct F-tests of their joint significance in the first stage of the 2SLS regressions. Secondly, with respect to the exogeneity of our instrumental variables, we present overidentification tests (Basmann, 1960). Besides these empirical tests, we conduct a sensitivity analysis in which alternative combinations of instrumental variables are used to prove that our identification does not hinge on one or two particular instruments.

In addition to being the first study in the literature on (general) smartphone use and

[3] In particular, we control for household wealth by means of our controls for paternal education level. Interestingly, from Panel C of Table 1, it can be seen that smartphone use hardly varies by paternal education level. The same is true with respect to our instrumental variables, i.e. they do not seem to be substantially correlated with the household's socioeconomic status.

educational performance to apply a statistical technique that controls for unobserved determinants of academic success, in our analyses we also control for a set of individual performance determinants that is larger than those used in the previous research mentioned in Section 1. Consequently, we minimise the number of factors influencing both smartphone use and academic performance that are omitted from the regression analysis and estimate the effect of smartphone use within homogeneous subgroups of individuals. Thereby, the ordinary least squares (OLS) estimates to which we compare our 2SLS estimates should already approximate the true effect of smartphone use on educational performance (for our sample) more closely than the corresponding estimates reported in previous studies.

3. Results

Table 2 presents the main estimation results of our benchmark analysis. This analysis comprises six regressions in which our main outcome variable, i.e. the respondent's average score on her/his completed exams, is explained by diverging independent variables (i.e. the overall smartphone use scale in models (1) and (2), smartphone use while attending class in models (3) and (4), and smartphone use while studying in models (5) and (6)) and all control variables mentioned in Panel C of Table 1. In columns (1), (3), and (5), we present OLS estimates, while in columns (2), (4), and (6), we present—our preferred—2SLS estimates exploiting the variation in all instruments listed in Panel B of Table 1. The full estimation results of model (2) are shown in Table A1 in Appendix A.

<Table 2 about here>

Irrespective of the estimation method used and the indicator of smartphone use chosen, we find negative coefficients of this indicator, which are significantly different from 0 at least at the 5% significance level. According to our 2SLS estimates in column (2) of Table 2, a unit increase on the overall smartphone use scale yields a decrease in exam score by 0.981 points ($p = 0.004$), *ceteris paribus*. In other words, given that the standard deviation (SD) of the overall smartphone use scale is 0.925, an increase on the overall smartphone use scale with one standard deviation decreases the average exam score by 1.061 (i.e. 0.981/0.925) points.

In addition, a one-standard-deviation increase on the scales with respect to smartphone use while attending class (SD = 1.724) and studying (SD = 1.586) yields a decrease in the average exam score with 0.512 (i.e. 0.883/1.724) and 0.449 (i.e. 0.712/1.586) points, respectively.

Interestingly, the magnitude of these 2SLS estimates is more than twice that of the corresponding OLS estimates. This suggests that university students with a relatively high smartphone use are a negatively selected subpopulation—negatively selected with respect to unobserved success determinants of academic performance—of the overall population of university students.[4] The need to control for unobserved heterogeneity in this context is also revealed by the p-values of the Hausman endogeneity tests we performed based on models (2), (4), and (6). Exogeneity of the adopted smartphone use indicators is, even after controlling for a large set of controls, rejected at the 5% significance level for model (4), rejected at the 10% significance level for model (6), and close to rejection at the 10% significance level for model (2). Moreover, Table 2 provides empirical support for the two crucial assumptions underlying our 2SLS approach mentioned in Section 2.3. Firstly, the used instruments are significant predictors of our smartphone use indicators—the p-value of the related F-test is always 0.000. Secondly, the Basmann overidentification test is never (close to) significant, supporting the exogeneity of the used instruments with respect to exam scores.

We briefly discuss some secondary results concerning the other determinants of academic success adopted in our models as controls. Table A1 shows that exam scores are higher among those students (i) starting at university at a younger age (*ergo*, with less or no grade retention during their secondary education), (ii) having Dutch as the main language spoken at home, (iii) not having divorced parents, (iv) showing a higher academic motivation, (v) living in a student room, (vi) living closer to the university, and (vii) having graduated from secondary education with high marks. A structural interpretation of the coefficients for these control variables is hazardous, however, as they might be endogenous to educational performance.

In what follows, we report on the results of two analyses performed to check the robustness of our benchmark analysis. In these sensitivity analyses, we rely on the overall

[4] We provide an alternative explanation when we discuss our research limitations in Section 4.

smartphone use scale as the independent variable, but the conclusions are the same when relying on the other two smartphone use indicators.

Firstly, we test the robustness of our results for the use of alternative outcome variables, i.e. the respondents' average scores on their potential exams (instead of completed exams) and the fraction of completed exams they pass. The OLS and 2SLS estimates with respect to the former alternative outcome variable are presented in columns (3) and (4) of Table 3, respectively, while the corresponding estimates with respect to the latter alternative outcome variable are presented in columns (5) and (6). To facilitate comparison between these estimation results and those in our benchmark analysis, we adopt columns (1) and (2) of Table 2 as columns (1) and (2) of Table 3. The results in column (4) are very close to those in column (2): a unit increase on the overall smartphone use scale decreases the exam score averaged over all potential exams with 0.848 points ($p = 0.014$). In addition, a unit increase on the overall smartphone use scale yields a decrease in the respondents' fraction of passed exams by 7.6 percentage points ($p = 0.044$), *ceteris paribus*. So, higher smartphone use does not only negatively affect exam scores but these lower exam scores also result in a higher probability of failing courses.

<Table 3 about here>

Secondly, we test the robustness of our results for the use of alternative sets of instrumental variables to identify our 2SLS estimates of the effect of smartphone use on exam scores. More concretely, in Table 4, we present the main estimation results of six 2SLS models, in which, starting from the specification of model (2) in our benchmark analysis, two out of four (clusters of) instruments are dropped. Stated otherwise, identification of regressions (2) to (7) of Table 4 is based on two out of the four (clusters of) instruments used in model (2) of Table 2 only. However, our findings turn out to be fairly independent of which set of instruments is used.[5]

<Table 4 about here>

[5] The somewhat lower significance of the effect of smartphone use in Column (6) and Column (7) of Table 4 may be related to a weak instrument problem (as supported by the p-value of the F-test, which is in these cases slightly higher than 0.000; Angrist and Pischke, 2008).

4. Conclusions

In this study, we contributed to recent literature concerning the association between smartphone use and educational performance by providing the first causal estimates of the effect of the former on the latter. To this end, we analysed unique data on 696 first-year university students in Belgium. We found that a one-standard-deviation increase in their overall smartphone use yields a decrease in their average exam score of about one point (out of 20). This negative relationship is robust to the use of alternative indicators of smartphone use and academic performance. As our results add to the literature evidence for heavy smartphone use not only being associated with lower exam marks but also *causing* lower marks, we believe that policy-makers should at least invest in information and awareness campaigns to highlight this trade-off.

We end this article by acknowledging its main limitations. Firstly, we measured the impact of smartphone use on exam scores for first-year university students attending classes in 11 study programs at three faculties in Belgium. Although we have no *a priori* reasons to expect that the relationship between smartphone use and academic performance would be different for other groups of students and/or other regions, our results cannot be automatically generalised to these other groups. Therefore, we are in favour of studies complementing our findings via similar investigations based on data from other kind of students and other regions.

Secondly, even when instrumental variables are valid—and empirical tests supported that this was the case in our analyses—2SLS estimations always only isolate a local average treatment effect (LATE; Angrist and Pischke, 2008). That is, the effect of smartphone use measured in this study was identified based only on the respondents whose smartphone use was affected by the included instrumental variables. This is an alternative explanation for our 2SLS estimates being of a higher magnitude than the corresponding OLS estimates. In this respect, however, it is important to recall that the higher smartphone use effects found based on our preferred approach were independent of which particular set of instruments was adopted. Nevertheless, we look forward to future work measuring the causal impact of smartphone use on academic performance using other statistical approaches (e.g. fixed-effects estimations exploiting longitudinal data).

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Appendix A: Additional Tables

<Table A1 about here>

Table 1. Data Description

	(1) Average	(2)	(3)	(4)
	Full sample N = 696	Subsample: Overall smartphone use below average N = 333	Subsample: Overall smartphone use above average N = 363	Difference: (3) – (2)
A. Smartphone use				
Overall smartphone use	5.701	4.970	6.372	1.402*** [30.602]
Smartphone use while attending class	4.499	3.934	5.017	1.083*** [8.709]
Smartphone use while studying	3.198	2.958	3.419	0.461*** [3.866]
B. Predictors of smartphone use				
4G technology on smartphone	0.846	0.769	0.917	0.149*** [5.540]
Download volume of 1GB or more	0.451	0.390	0.507	0.116*** [3.102]
Operator: Proximus	0.352	0.378	0.328	-0.051 [1.394]
Operator: Base	0.109	0.099	0.118	0.019 [0.817]
Operator: Orange	0.260	0.237	0.281	0.044 [1.314]
Operator: Telenet	0.220	0.219	0.220	0.001 [0.037]
Operator: other	0.059	0.066	0.052	-0.013 [0.767]
Perceived quality of WiFi in classrooms	3.555	3.491	3.614	0.123* [1.915]
Paying smartphone costs herself/himself	0.168	0.159	0.176	0.017 [0.604]
C. Control variables				
Program: University of Antwerp	0.365	0.366	0.364	-0.003 [0.075]
Program: Ghent University, Business and Economics	0.352	0.372	0.333	-0.039 [1.077]
Program: Ghent University, Commercial Sciences	0.214	0.204	0.223	0.019 [0.608]
Program: Ghent University, Public Administration and Management	0.069	0.057	0.080	0.023 [1.187]
Program: University of Antwerp, Business Economics	0.151	0.141	0.160	0.019 [0.686]
Program: University of Antwerp, Economic Policy	0.017	0.024	0.011	-0.013 [1.316]
Program: University of Antwerp, Business Engineering	0.014	0.018	0.011	-0.007 [0.774]
Program: University of Antwerp, Management Information Systems	0.053	0.057	0.050	-0.007 [0.438]
Program: University of Antwerp, Communication Studies	0.042	0.045	0.039	-0.006 [0.427]
Program: University of Antwerp, Political Science	0.016	0.006	0.025	0.019** [1.988]
Program: University of Antwerp, Social and Economic Sciences	0.043	0.036	0.050	0.014 [0.879]
Program: University of Antwerp, Sociology	0.029	0.039	0.019	-0.020 [1.559]
Female	0.510	0.508	0.512	0.005 [0.129]

Age	18.057	18.051	18.063	0.012 [0.367]
Foreign origin	0.152	0.123	0.179	0.056** [2.055]
Dutch is not main language at home	0.099	0.081	0.116	0.035 [1.527]
Highest diploma father: no tertiary education	0.358	0.363	0.353	-0.011 [0.295]
Highest diploma father: tertiary education outside college	0.299	0.294	0.303	0.009 [0.251]
Highest diploma father: tertiary education in college	0.343	0.342	0.344	0.002 [0.056]
At least one parent passed away	0.022	0.018	0.025	0.007 [0.614]
Divorced parents	0.208	0.192	0.223	0.031 [1.004]
Number of siblings: none	0.096	0.090	0.102	0.012 [0.528]
Number of siblings: one	0.510	0.514	0.507	-0.007 [0.174]
Number of siblings: two	0.295	0.297	0.292	-0.005 [0.153]
Number of siblings: more than two	0.099	0.099	0.099	0.000 [0.003]
In a relationship	0.355	0.387	0.325	-0.062* [1.717]
General health: (fairly) bad	0.040	0.024	0.055	0.031** [2.088]
General health: fairly good	0.575	0.565	0.584	0.019 [0.518]
General health: very good	0.385	0.411	0.361	-0.051 [1.368]
Academic motivation scale	4.969	4.936	4.999	0.064 [1.400]
Executive functioning problems scale	1.801	1.772	1.828	0.056 [1.587]
Using laptop to take notes in class	0.171	0.123	0.215	0.092*** [3.231]
Living in a student room	0.343	0.378	0.311	-0.067* [1.864]
Distance between home and university (in km)	34.100	36.402	31.988	-4.414** [2.316]
Program in secondary education: Economics - languages/sports	0.283	0.234	0.328	0.094*** [2.749]
Program in secondary education: Economics - maths	0.216	0.246	0.187	-0.059* [1.891]
Program in secondary education: Ancient languages	0.188	0.201	0.176	-0.025 [0.839]
Program in secondary education: Exact sciences - maths	0.147	0.153	0.140	-0.013 [0.471]
Program in secondary education: other	0.167	0.165	0.168	0.003 [0.102]
General end marks in secondary education: less than 70%	0.374	0.339	0.405	0.066* [1.789]
General end marks in secondary education: between 70% and 80%	0.494	0.502	0.488	-0.014 [0.366]
General end marks in secondary education: more than 80%	0.132	0.159	0.107	-0.052** [2.016]
D. Academic performance				
Average score: completed exams	10.973	11.550	10.443	-1.107*** [4.620]
Average score: potential exams	10.888	11.442	10.380	-1.062*** [4.355]
Fraction of exams passed	0.646	0.689	0.606	-0.083*** [3.219]

Notes. See Section 2.2 for a description of the data. T-tests are performed to test whether the differences presented in Column (3) are significantly different from 0. *** (**) ((*)) indicates significance at the 1% (5%) ((10%)) significance level. T-statistics are between brackets.

Table 2. Main Estimation Results: Benchmark Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dependent variable	Average score: completed exams	Average score: completed exams	Average score: completed exams	Average score: completed exams	Average score: completed exams	Average score: completed exams
Instrumental variables	-	All	-	All	-	All
Overall smartphone use	-0.462*** (0.113)	-0.981*** (0.338)				
Smartphone use while attending class			-0.260*** (0.062)	-0.883*** (0.288)		
Smartphone use while studying					-0.134** (0.068)	-0.712** (0.329)
Additional control variables	All	All	All	All	All	All
Hausman endogeneity test (p-value)	-	0.108	-	0.020	-	0.066
First stage: F-test of instruments' joint significance (p-value)	-	0.000	-	0.000	-	0.000
Basmann overidentification test (p-value)	-	0.603	-	0.872	-	0.347
Number of observations	696	696	696	696	696	696

Note. OLS (2SLS) stands for ordinary least squares (two-stage least squares). See Section 2.2 for a description of the data. See Table A1 for the full regression results of model (2). The presented results are coefficient estimates, with standard errors in parentheses. *** (**) ((*)) indicates significance at the 1% (5%) ((10%)) significance level.

Table 3. Main Estimation Results: Alternative Outcome Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dependent variable	Average score: completed exams	Average score: completed exams	Average score: potential exams	Average score: potential exams	Fraction of exams passed	Fraction of exams passed
Instrumental variables	-	All	-	All	-	All
Overall smartphone use	-0.462*** (0.113)	-0.981*** (0.338)	0.432*** (0.116)	-0.848** (0.345)	-0.031** (0.013)	-0.076** (0.038)
Additional control variables	All	All	All	All	All	All
Hausman endogeneity test (p-value)	-	0.108	-	0.209	-	0.210
First stage: F-test of instruments' joint significance (p-value)	-	0.000	-	0.000	-	0.000
Basmann overidentification test (p-value)	-	0.603	-	0.705	-	0.977
Number of observations	696	696	696	696	696	696

Note. OLS (2SLS) stands for ordinary least squares (two-stage least squares). See Section 2.2 for a description of the data. The presented results are coefficient estimates, with standard errors in parentheses. *** (**) ((*)) indicates significance at the 1% (5%) ((10%)) significance level.

Table 4. Main Estimation Results: Alternative Instrumental Variable Combinations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Dependent variable	Average score: completed exams	Average score: completed exams	Average score: completed exams	Average score: completed exams	Average score: completed exams	Average score: completed exams	Average score: completed exams
Instrumental variables	All	4G technology on smartphone, Download volume of 1GB or more, Operator: Base, Operator: Orange, Operator: Telenet, and Operator: other	4G technology on smartphone and Perceived quality of WiFi in classrooms	4G technology on smartphone and Paying smartphone costs herself/himself	Download volume of 1GB or more, Operator: Base, Operator: Orange, Operator: Telenet, Operator: other, and Perceived quality of WiFi in classrooms	Download volume of 1GB or more, Operator: Base, Operator: Orange, Operator: Telenet, Operator: other, and Paying smartphone costs herself/himself	Perceived quality of WiFi in classrooms and Paying smartphone costs herself/himself
Overall smartphone use	-0.981*** (0.338)	-0.885** (0.349)	-0.907** (0.375)	-0.766** (0.391)	-1.407*** (0.526)	-1.201* (0.616)	-1.844* (0.997)
Additional control variables	All	All	All	All	All	All	All
Hausman endogeneity test (p-value)	0.108	0.197	0.222	0.428	0.059	0.221	0.120
First stage: F-test of instruments' joint significance (p-value)	0.000	0.000	0.000	0.000	0.000	0.001	0.005
Basmann overidentification test (p-value)	0.603	0.567	0.237	0.394	0.635	0.558	0.416
Number of observations	696	696	696	696	696	696	696

Note. OLS (2SLS) stands for ordinary least squares (two-stage least squares). See Section 2.2 for a description of the data. The presented results are coefficient estimates, with standard errors in parentheses. *** (**) ((*)) indicates significance at the 1% (5%) ((10%)) significance level.

Table A1. Full Estimation Results: 2SLS Regression of Average Completed Exam Score on Smartphone Use

Stage	First	Second
Dependent variable	Overall smartphone use	Average score: completed exams
Instruments	All	All
Overall smartphone use		-0.981*** (0.338)
4G technology on smartphone	0.630*** (0.095)	
Download volume of 1GB or more	0.237*** (0.070)	
Operator: Proximus		
Operator: Base	0.215* (0.128)	
Operator: Orange	0.114 (0.087)	
Operator: Telenet	-0.015 (0.092)	
Operator: other	0.035 (0.154)	
Perceived quality of WiFi in classrooms	0.103** (0.043)	
Paying smartphone costs herself/himself	-0.008 (0.095)	
Program: University of Antwerp	-0.056 (0.116)	0.080 (0.341)
Program: Ghent University, Business and Economics (reference)		
Program: Ghent University, Commercial Sciences	0.076 (0.107)	1.829*** (0.321)
Program: Ghent University, Public Administration and Management	0.212 (0.149)	1.001** (0.454)
Program: University of Antwerp, Business Economics (reference)		
Program: University of Antwerp, Economic Policy	-0.200 (0.268)	0.506 (0.808)
Program: University of Antwerp, Business Engineering	0.289 (0.296)	-0.324 (0.880)
Program: University of Antwerp, Management Information Systems	-0.006 (0.181)	0.169 (0.537)
Program: University of Antwerp, Communication Studies	0.017 (0.192)	-0.467 (0.573)
Program: University of Antwerp, Political Science	0.535* (0.288)	1.589* (0.886)
Program: University of Antwerp, Social and Economic Sciences	0.084 (0.186)	2.159*** (0.560)
Program: University of Antwerp, Sociology	-0.258 (0.220)	-0.146 (0.662)
Female	-0.052 (0.071)	-0.333 (0.213)
Age	-0.019 (0.081)	-0.697*** (0.243)
Foreign origin	0.191 (0.124)	-0.624* (0.371)
Dutch is not main language at home	0.045 (0.151)	-0.992** (0.445)
Highest diploma father: no tertiary education (reference)		
Highest diploma father: tertiary education outside college	0.084 (0.085)	0.326 (0.254)
Highest diploma father: tertiary education in college	0.142* (0.084)	0.259 (0.253)
At least one parent passed away	-0.325 (0.239)	-0.286 (0.717)
Divorced parents	0.009 (0.086)	-0.706*** (0.257)
Number of siblings: none (reference)		
Number of siblings: one	-0.166 (0.119)	-0.253 (0.359)
Number of siblings: two	-0.168 (0.127)	-0.280 (0.383)
Number of siblings: more than two	-0.229 (0.153)	-0.331 (0.462)
In a relationship	-0.076 (0.071)	0.194 (0.215)
General health: (fairly) bad (reference)		
General health: fairly good	-0.458** (0.176)	0.357 (0.548)
General health: very good	-0.488*** (0.181)	0.566 (0.562)
Academic motivation scale	0.143** (0.058)	0.498*** (0.181)
Executive functioning problems scale	0.005 (0.076)	-0.336 (0.228)
Using laptop to take notes in class	0.168* (0.095)	0.197 (0.295)
Living in a student room	-0.045 (0.085)	0.686*** (0.253)
Distance between home and university (in km)	-0.001 (0.002)	-0.015*** (0.005)
Program in secondary education: Economics - languages/sports	0.131 (0.109)	-0.404 (0.330)
Program in secondary education: Economics - maths	-0.011 (0.120)	1.405*** (0.360)
Program in secondary education: Ancient languages	0.011 (0.122)	1.256*** (0.366)
Program in secondary education: Exact sciences - maths	0.172 (0.137)	1.550*** (0.411)

Program in secondary education: other (reference)		
General end marks in secondary education: less than 70% (reference)		
General end marks in secondary education: between 70% and 80%	0.074 (0.076)	2.029*** (0.226)
General end marks in secondary education: more than 80%	-0.112 (0.116)	3.166*** (0.354)
Intercept	4.749*** (1.532)	24.931*** (4.965)
Hausman endogeneity test (p-value)	-	0.108
F-test of instruments' joint significance (p-value)	0.000	-
Basmann overidentification test (p-value)	-	0.603
Number of observations	696	696

Note. See Section 2.2 for a description of the data. The presented results are coefficient estimates, with standard errors in parentheses. *** (**) ((*)) indicates significance at the 1% (5%) ((10%)) significance level.