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Social Media and Academic Performance: Does the Intensity of Facebook Activity Relate to Good Grades?**

Abstract

We analyze how Facebook use and students' social network positions within it relate to their academic performance. We use a unique data set obtained from a survey of students' perceptions, actual Facebook connections to measure social network positions, and objective grades provided by the university registrar to measure academic performance. We find that Facebook activities during class relate negatively to academic performance, that students located in densely connected subnetworks earn better grades, and that in contrast to female students, male students benefit from a general use of Facebook, particularly if they are highly connected.

JEL Classification: D83, D85, M3, M30, M31.

Keywords: Academic Performance; Facebook; Social Media; Social Network Analysis.

1 Introduction

The popularity of social media, such as Facebook, LinkedIn, Twitter, and Xing, continues to grow, providing people with amazing opportunities to interact through social networks (Hinz, Skiera, Barrot, and Becker (2011); Junco (2013); Messerschmidt, Berger, and Skiera (2010); Nadkarni and Hofmann (2012)). Many people happily make use of these opportunities by spending significant time on social media (Schulze, Schöler, and

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Skiera (2014)). For example, roughly one in three Germans is active on Facebook, and Americans spend on average more than 20 minutes per day on Facebook. We can capture the different roles that people can have in these networks by sociometric measures such as degree centrality, betweenness and closeness centrality.

Through the social connections that people typically maintain on these platforms, individuals can gain access to resources that may be key to their professional success (Baldwin, Bedell, and Johnson (1997)), including information and links to important others (Burt (1992a)) and functional communication networks that lead to effective organizational forms (Rogers (1979)). Yet with limited time available, too much time spent socializing also could have negative effects on professional success (Astin (1984); Chickering and Gamson (1987); Junco (2012)). For example, for students, who are perhaps the most intensive users of social media, interacting on the platform, playing video games and using other electronic media (Jacobsen and Forste (2011)), expressing themselves, and maintaining friendships are time-intensive acts that might limit the time available for studying, thus possibly harming their academic performance (Mihaly (2009)).

To clarify how social media activities relate to academic performance, we analyze the relation of academic performance to social media activity and a person's social network position. To accomplish this aim, we also provide an overview of measures that characterize social network positions in full and egocentric social networks.

To our knowledge, our empirical study is the first to investigate this relation among German students. Differences between German and American students might occur because they use different kinds of content, e.g., because of the stronger privacy concerns in Germany or cultural differences. As far as we know, ours is also the first study to analyze actual social network positions, which we measure with students' Facebook data and egocentric networks. Furthermore, we are also the first to analyze the impact of interactions between gender and measures of social network positions on academic performance. Finally, our research is among the first to use actual academic grades, which were provided to us by a university registrar. Actual grades supply a higher validity than do self-reported grades (Junco (2012)). This use of diverse data sources contrasts sharply with those studies that use only survey data.

The paper is organized as follows: In Section 2, we consider important social network analysis metrics. In Section 3 we summarize prior research that tries to specify the links between these metrics and student performance. From these analyses, we derive our hypotheses, which we test in Section 4 by using an empirical study with students at a large German university. In Section 5 we summarize our main findings and conclude.

2 Social Network Analysis

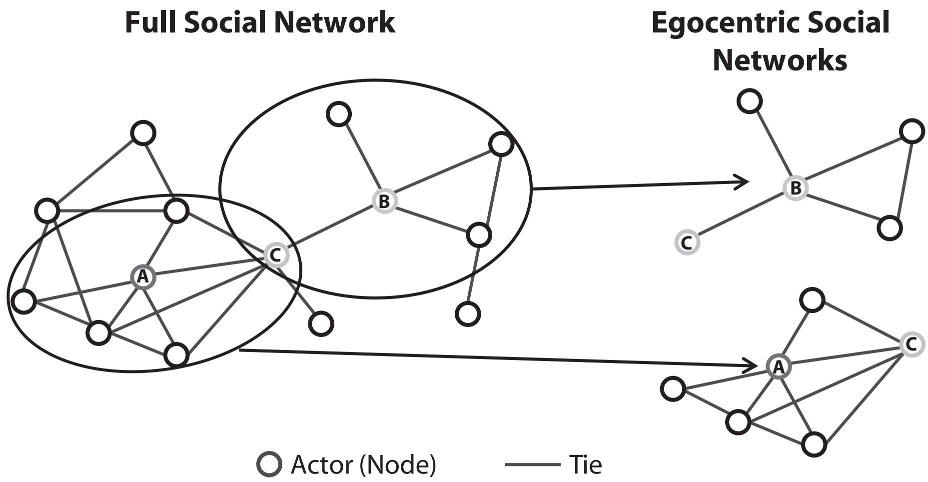
In modern sociology, social network analysis defines social relations by using a network theoretic approach (Freeman (2006)). A basic network consists of actors (or nodes) and the connections (or relations) among them, which are represented as ties. *Figure 1* offers examples of social networks in which each tie represents a connection between two actors and indicates the directionality and intensity of their link. Social network analysis uses information about these connections to characterize the whole network, the position of each social entity in that network, and the local network of each social entity (Freeman (1979)). A social entity can be an individual, such as a consumer or employee, an organization, or an organizational unit. Two basic types of networks appear frequently in business research: full social networks and egocentric social networks. Different metrics are useful to characterize individuals in these two types of networks.

2.1 Full and Egocentric Social Networks

A full social network consists of all the network's nodes and ties within a given boundary, such as the entire network of students attending a university or enrolled in a particular department or class. In principle, the whole population of the planet could be considered a single social network, although it would be difficult to capture all these connections. The analysis of a full social network usually requires some boundary specification, called network specification strategy (Laumann, Marsden, and Prensky (1992)). Unlike a full social network, an egocentric social network results from the perspective of one actor, that is, the ego (Van den Bulte and Wuyts (2007)). This type of network encompasses only the ego and the direct connections that might be alter egos or peers, and the relationships that exist among these connections (Burt (1984)).

The left-hand panel of *Figure 1* depicts a full social network of 14 actors; the right-hand panel shows the egocentric social networks of Actors A and B. By definition, egocentric social networks are embedded in a full social network, as illustrated by *Figure 1*. Focusing on isolated networks of Actors A and B in the form of egocentric social networks makes it easier to obtain information, e.g., from surveys of egos, Burt (1984); downloaded data from Facebook using NodeXL; maps provided by LinkedInMaps, the Facebook app "MyFnetwork," the "VK online graph" on the vkontakte social network. However, this focus ignores relationships across egocentric social networks. For example, it cannot identify how Actor C in *Figure 1* connects the two subnetworks.

Figure 1: Full Social Network and Two Egocentric Social Networks



2.2 Metrics to Describe Each Actor in a Social Network

Centrality measures describe the position of an actor in a social network, which may relate to his or her importance in the network (Van den Bulte and Wuyts (2007); Schlereth, Barrot, Skiera, and Takac (2013)). The most prominent centrality measures are degree, betweenness, and closeness (Freeman (1979)). The degree of centrality indicates the number of direct connections an actor (ego) has in a full network (egocentric network). A high degree of centrality indicates popularity. In *Figure 1*, the degree of centrality values for Actors A and B are 5 and 4, respectively, in both the full social network and their respective egocentric social networks.

Betweenness centrality captures the extent to which an actor falls between the dispersed parts of the social network. We measure betweenness by measuring the degree of the actor's placement on the shortest path between any two actors (Freeman (1979)). An actor with high betweenness centrality is a broker, who can access and pass information across different parts of the social network (Scott (2000)). In *Figure 1*, Actor A is on 5.67 of the shortest paths in the full social network, Actor B is on 39, and Actor C is on 48.17. In the egocentric social networks, A is on the 3 shortest paths, and B is on 7 shortest paths between any pair of alter egos.

Closeness centrality measures the inverse of the sum of the shortest distances from an actor to all the other actors he or she can reach within a social network. Thus, closeness centrality indicates communication efficiency (Freeman (1979)). Closeness centrality is not applicable to egocentric social networks, because only connections between the ego and his or her neighbors and their neighbors come into play (Everett and Borgatti (2005)).

In *Figure 1*, the closeness centrality of Actors A and B in the full social network are 0.038 and 0.04, respectively (Actor C's closeness centrality is 0.048).

The concept of local density provides the clustering coefficient, which measures the density of the egocentric social network of one actor. (We note that the focal actor is not included in this calculation.) In *Figure 1*, the clustering coefficients for the egocentric social networks of Actors A and B are 5/(5 ´ 4 / 2) = 50% and 1/(4 ´ 3 / 2) = 16.67%, respectively.

2.3 Metrics to Characterize the Structure of a Social Network

The number of nodes and connections are the elements that characterize the structure of the full social network. For example, the full social network in *Figure 1* has 14 actors (nodes) and 22 connections. Density measures the proportion of actual to possible connections (Van den Bulte and Wuyts (2007)). For 14 actors, the number of possible connections is 14 ´ (14 – 1) / 2 = 91, so the density is 22/91, 24.18%.

We use the average values of the metrics that describe the position of each actor in a social network to characterize the structure of the social network. In the full social network in *Figure 1*, the average degree centrality is 3.14, the average betweenness centrality is 9.29, the average closeness centrality is 0.03, and the average clustering coefficient is 0.44. Another measure is the maximum geodesic distance, or diameter. It equals 5, because it takes a maximum of five connections to get from one actor to another in the social network. The average geodesic distance is 2.25.

3 Conceptual Background

3.1 Literature Review

Previous research on the relation between social media activities and students' academic achievement is growing, but still relatively scarce and concentrated on U.S. students. *Table 1* summarizes the research findings to date. Despite some variation, most studies find a negative relation between time spent on Facebook and academic performance. Some differences might be driven by measurement variance, because most of the earlier studies rely on a self-reported, non-continuous, grade-based measurement of performance grades (see Junco (2012)). Other differences might occur because not all of the studies control for prior grades in high school as Pasek, More, and Hargittai (2009) do. Previous studies do not measure the effect of social network positions on Facebook, and none of them identify causality (see Junco (2012)). This latter lacuna is a limitation that remains valid for our study.

Table 1: Previous Research into the Relation of Social Media Activities and Academic Performance

Study	Main Finding	Measure of Academic Achievement	Measure of Social Media Activities	Measure of Social Network Position
Jacobsen and Forste (2011)	Negative relation between exposure to social network sites and academic performance	Self-reported GPA, four-point scale	Self-reported time-diary on use of electronic media	None
Junco (2012)	Negative relation between time spent on Facebook and academic performance	GPA provided by university registrar	Self-reported time spent on Facebook	None
Karpinski, Kirschner, Ozer, Mellott, and Ochwo (2013)	Negative relation between social network use and academic performance	Self-reported GPA	Self-reported measure of social network use	None
Kirschner and Karpinski (2010)	Negative relation between Facebook use and academic performance	Self-reported GPA	Self-reported measure of Facebook use	None
Pasek, More, and Hargittai (2009)	No relation between Facebook use and academic performance	Self-reported GPA, on eight-point scale	Self-reported dichotomous measure of Facebook use	None
Paul, Baker, and Cochran (2012)	Negative relation between time spent on social networks and academic performance	Self-reported GPA	Self-reported measure of time spent on social networks	None

Notes: GPA = grade point average.

3.2 Hypotheses

As mentioned in the previous section, prior research indicates that Facebook use might relate negatively to academic performance. An explanation of this negative relation notes that time is a limited resources(e.g., Falkinger (2007)), so time on Facebook, and particularly time spent on gaming and self-expression, decreases the time available for learning. Smith and Wilson (2005) find that workers' functional IQs fall ten points when they are distracted by external elements, such as ringing telephones and incoming e-mails. Karpinski, Kirschner, Ozer, Mellott, and Ochwo (2013) summarize research that shows that frequently switching between tasks leads to poorer learning and performance on tasks than serial completion of the same tasks. Therefore, we hypothesize:

H1. *The intensity of Facebook use relates negatively to academic performance.*

In addition, the use of Facebook in class distracts from learning (see Paul, Baker, and Cochran (2012)), so we predict:

H2. *Facebook use in classes relates negatively to academic performance.*

However, more favorable arguments suggest Facebook use can enable information exchanges and help students prepare for exams. Many streams of literature in social network analysis, marketing, and sociology assert that social positions determine information access. For example, Borgatti and Foster (2003) argue that cohesive subgroup membership in a network positively affects performance, and that the magnitude of connectivity in a subgroup can be captured by the clustering coefficient. Members of such densely connected cliques tend to achieve better local cooperation (Chwe (2000)); accordingly, students in cliques might share exam-relevant information. Furthermore, access to cliques has a strong impact on members' performance and their position in society (Oppenheim (1955)). Thus, we hypothesize:

H3. *Students in closely connected subnetworks (measured by high clustering coefficients) achieve better academic performance than do those in loosely connected networks.*

People with a high degree of centrality, and thus more links to others, also tend to have greater access to information (Burt (1992b); Hinz and Spann (2008); Hinz et al. (2011)). Research in management, public administration, and organizational sociology (Hinz, Spann, and Hann (2014); Meier and O'Toole (2003); Schalk, Torenvlied, and Allen (2010)) asserts that agents with a high degree of centrality have ample access to resources and potential for learning and cooperation, which ultimately may lead to better academic performance. Because the number of friends might relate positively to academic performance, we predict:

H4. *The number of friends on Facebook (measured by degree centrality) relates positively to academic performance.*

In our study we control for the high school grade point average (HSGPA, or Abiturnote in German), which captures students' latent capabilities and serves as a good predictor of academic performance at university (Junco (2012)). We also control for age ("age") and semester ("semester"), because a student's average grades may vary in earlier compared to later semesters; and for students' part-time jobs ("PartTimeJob"), which may have a negative impact on academic performance ("AcademicPerformance"). Additional control variables refer to academic effort ("effort") and whether the students use Facebook to stay in contact with fellow students ("UseFBforUniversity"). Furthermore, the time at which the student started using Facebook ("AdoptionTime") may have an impact on the academic performance.

These considerations lead to the following model that we estimate in the following empirical study and in which index *i* describes the respective student:

$$\begin{aligned} AcademicPerformance_i = {} & \beta_0 + \beta_1 \cdot FBUseInGeneral_i + \beta_2 \cdot FBUseDuringClass_i \\ & + \beta_3 \cdot Clustering_i + \beta_4 \cdot Degree_i + \beta_5 \cdot HSGPA_i + \beta_6 \cdot Gender \\ & + \beta_7 \cdot Semester_i + \beta_8 \cdot Age_i + \beta_9 \cdot PartTimeJob_i + \beta_{10} \cdot Effort \\ & + \beta_{11} \cdot UseFBforUniversity_i + \beta_{12} \cdot AdoptionTime_i + \varepsilon_i, \end{aligned} \tag{1}$$

where *FBUseInGeneral* denotes Facebook use in general, and *FBUseDuringClass* the use of Facebook during classes (see also *Table 3*). *Clustering* serves as the clustering coefficient, *Degree* is degree centrality, and *Gender* is defined as one for females and zero for males.

4 Empirical Study

To analyze the relation between the use of Facebook and students' academic performance, we examine if more successful students are more connected on Facebook than are less successful students. In contrast with the studies listed in *Table 1*, for our data sources we rely on surveys, academic grades provided by the university registrar, and social position on Facebook and distinguish between Facebook use in general and in class. In addition, we focus on German instead of American students and incorporate their social positions, which may be decisive for their academic performance.

4.1 Data

The subjects of our empirical study are bachelor-degree students who attended a major German university in early 2012. To facilitate the comparison of their academic achievements, we selected students studying business and economics. For each student we collected data from three sources. First, we required each student to respond to a survey conducted with the online survey platform DISE (Schlereth and Skiera (2012)). Second, each student submitted a copy of his or her academic transcript from the university registrar. Third, each student provided access to his or her egocentric network on Facebook, through an interface with NodeXL software. Thus, in contrast to most of the earlier studies, we were able to collect observable, reliable information about students' grades and social networks on Facebook. Each student received €10 in compensation for his or her effort, and a third party deleted personal information (e.g., students' names) from our data set.

Of the 117 students who agreed to participate, five stopped their participation before the end of the study, and technical problems prevented us from collecting Facebook data from 9 participants. Hence, we built our analysis on the remaining 103 participants, confirming that they took sufficient time to answer the online questionnaire. *Table 2* describes the sample in more detail.

Table 2: Sample Description

Variable	Mean	Standard Dev.
Academic performance (average grades at university)[a]	2.46	.54
High school grade point average (*Abiturnote*)[a]	1.99	.42
Gender (0: Male; 1: Female)	0.48	
Semester	5.12	1.37
Age	22.55	1.74
Part-time job (hours per week)	9.23	9.53
Degree (number of friends)	350.14	159.79
Clustering coefficient	0.09	.04

Notes: a Scale from 1.0 (best) to 5.0 (fail). $N = 103$.

The sample compares well with the larger population of students in business and economics: 43.2% of all students in the winter semester of the 2011–2012 school year were women (48% in our sample). Moreover, their average age was 22.5 years, and on average they worked for outside jobs for 9.23 hours per week. They maintained an average of 350 friends on Facebook, although female students averaged 338 and male students averaged 361 friends on Facebook. The number of friends varied from 22 to 869.

To measure academic performance, we used the weighted average of all the grades noted on the official university transcript, according to the credit points associated with the respective course, which in turn reflected the time required to invest in each particular course. In this case, lower scores mean better academic performance: The best grade possible is 1.0; a 5.0 indicates a failed exam. The mean grade in our sample was 2.46; the best student earned a grade of 1.22, and the student with the worst grade showed a score of 3.66. Visual assessment see *Figure 2* as well as the Shapiro-Wilk normality test ($p > 0.33$) and the Shapiro-Francia normality test ($p > 0.47$) do not reject the null hypothesis of normality. The HSGPAs ranged from 1.0 to 3.3 with a mean of 1.99, so grades in high school were slightly better than those at university.

We measured Facebook use in general, use of Facebook during classes, effort toward studies, and use of Facebook for university contacts. As *Table 3* shows, the internal validity of the multi-item constructs is good; we used the average value of the respective items to reflect the value of the construct.

Figure 2: Distribution of Academic Performance (Dependent Variable, Measured by Weighted Average of Grades)

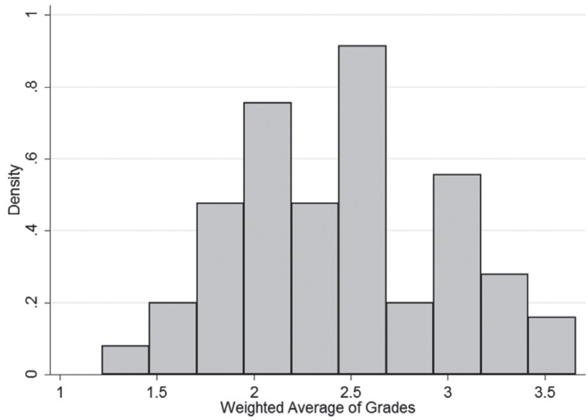


Table 3: Construct Description

Construct (Source)	Item	Mean	Corrected Item-to-Total Correlation	Cronbach's Alpha
Facebook use in general	I spend too much time on Facebook.	4.874	0.749	0.847
	On an average day I use Facebook … hours.	4.311	0.643	
	Compared to my friends, I do not use Facebook very frequently (reverse scale).	3.951	0.657	
	Facebook is an important part of my daily life.	4.670	0.729	
Use of Facebook during classes	I use Facebook during lectures ("Vorlesungen").	3.757	0.804	0.891
	I use Facebook during classes ("Übungen, Mentorien").	2.835	0.804	
Effort toward studies	I attend lectures ("Vorlesungen").	5.563	0.615	0.744
	I attend classes ("Übungen, Mentorien").	6.029	0.637	
	I study much more than my classmates.	3.544	0.416	
	I invest much time in preparing my lecture and classes.	3.816	0.593	
	I always prepare the exercises of my class.	3.019	0.322	
Use of Facebook for university contacts	I am in daily contact with my fellow students via Facebook.	4.427		

Notes: $N = 103$. Items measured on seven-point Likert scales from 1 (completely disagree) to 7 (completely agree).

4.2 Results

Before estimating our model, explorative analyses suggest that Facebook use and networking behavior are gender specific. Chow tests indicate that the coefficients for degree centrality, Facebook use, and effort expended on studies are different between men and women, so pooling is not adequate without further considerations. We address these differences by including interaction effects between gender and degree centrality, between gender and Facebook use, and between gender and effort.

We estimate a linear regression model with robust standard errors and obtain the results for the model outlined in Equation (1) plus interactions. *Table 4* shows the results. We also estimate several alternative models, the results of which are displayed in *Table 6*. In all models we used the Huber (1967) and White (1980) sandwich estimators to estimate the standard errors. Doing so enables us to deal with minor concerns about the potential failure to meet assumptions, such as normality or heteroscedasticity, or observations that exhibit large residuals, leverage, or influence. The point estimates of the coefficients are the same as in ordinary least squares (OLS), but the standard errors account better for the limitations of OLS due to heteroscedasticity or potential lack of normality.

Table 4: Determinants of Academic Performance

Independent Variable	Coefficient	Standard. Coeff.	Robust Standard Error	Change in R^2	*F*-test
Facebook use in general (H1)	-0.141***	-0.379	0.053	0.0002	0.02
Facebook use during classes (H2)	0.049*	0.181	0.027	0.0218	2.90*
Clustering coefficient (H3)	-2.397*	-0.161	1.244	0.0087	0.74
Degree (H4)	-0.001*	-0.216	0.000	0.0013	0.15
Degree × Gender	0.0007**	0.432	0.001	0.0009	0.10
FB use in general × Gender	0.202***	0.870	0.061	0.0003	0.04
Gender (0: Male; 1: Female)	-2.227***	-2.075	0.414	0.0512	5.09**
High school grade point average	0.650***	0.509	0.136	0.2832	43.55***
Semester	-0.113***	-0.305	0.034	0.0426	7.60***
Age	0.053*	0.171	0.029	0.0162	2.84*
Part-time job	-0.00003	-0.001	0.005	0.0000	0.00
Effort toward studies	-0.127**	-0.268	0.054	0.0118	1.70
Effort × Gender	0.211***	0.937	0.070	0.0388	8.64***
Use Facebook for university contacts	-0.042	-0.154	0.027	0.0153	2.38
Adoption time in months	0.001	0.034	0.004	0.0008	0.13
Constant	2.227***		0.650		
F-Value	9.090				
Prob > *F*	0.000				
R^2	0.493				
Root mean squared error (RMSE)	0.415				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, two-tailed significance.
Notes: The dependent variable was academic performance, measured by the weighted average of grades at the university. The Change in R^2 denotes the increases in R^2 from adding each additional variable in the order of their appearance in this table. The *F*-test depicts the significance of the change in R^2.

4.2.1 Relation between Facebook Use and Academic Performance

Table 4 shows that the R-square value for our full model is 49.3%, which is quite good. The F-value allows us to reject the null hypothesis that sets of coefficients are jointly zero ($p < 0.01$). The results do not support H1, which predicts that the intensity of Facebook use in general relates to lower academic performance. We find that males benefit academically from Facebook use ($p < 0.01$), but women who use Facebook intensively have a lower academic performance, captured by the interaction effect FB use in general × Gender ($p < 0.01$). We also check for nonlinear effects of Facebook use and estimate the model with a quadratic term for Facebook use, because a moderate level of Facebook use might relate positively to academic performance while excessive use might relate negatively. However, we find no significant linear or quadratic effects of Facebook use. One possible explanation for this finding could be the clear distinction between Facebook use in general and use in class, which seems relevant: The results shown in *Table 4* support H2 ($p < 0.1$) as Facebook use in class is associated with poorer grades.

4.2.2 Relation between Network Characteristics and Academic Performance

We find support for H3, our hypothesis that students who are located in a strong clique, as measured by a high clustering coefficient, earn better grades ($p < 0.1$). In such a clique, nearly everyone is connected to everyone else, and members tend to share information and trust one another (Hinz and Spann (2008); Krackhardt (1999)). In contrast, a collection of isolated individuals with few or no ties tend to have difficulties exchanging resources (Balkundi and Harrison (2006)). In our study context, this finding indicates that students in a strong clique use their relations to achieve better academic performance.

We find support for H4, which concerns the number of connections. Highly interconnected students exhibit better grades (-0.001, $p < 0.1$). Again, this result strongly supports a gender-specific effect of Facebook use. Women and men seem to use the social network differently, which may also explain differences in academic performance.

Female students achieve better grades on average ($p < 0.01$). The interaction effect Degree × Gender (0.001, $p < 0.05$) shows that the effect of degree on grades among male students is nullified for female students. Highly connected male students earn better grades, but female students who are similarly interconnected have relatively worse grades. This gender-specific finding is in line with previous research that indicates that men use their social contacts for networking purposes and thereby achieve greater career performance than women (e.g., Forret and Dougherty (2004)).

Studies on gender-specific communication and networking behavior also cite some strong differences between men and women (e.g., Brett and Stroh (1997); Dreher and Cox (2000); Schneer and Reitman (1997); Stroh, Brett, and Reilly (1992)). Forret and Dougherty (2004) find that involvement in networking behavior is more beneficial to men's career progress. The reason could be that women tend to exhibit expressive, social-emotional behavior, but men perform stereotypical male roles, behaving in non-emotional, instrumental ways (Athenstaedt, Haas, and Schwab (2004)). In our context, men might utilize their social capital through the use of Facebook while women use Facebook for socializing purposes. This statement is supported by the significant interaction between Facebook usage and gender ($p < 0.01$). While men connect to generate and exploit social capital, women groom their relationships, which requires more time (that could also be used for studying) than does the goal-oriented approach that men pursue.

4.2.3 Relation between Control Variables and Academic Performance

The coefficient for HSGPA (Abiturnote) is 0.65 and highly significant ($p < 0.01$); school grades provide good predictors of university performance. Moreover, students in later semesters achieved better grades ($p < 0.01$), likely due to a selection bias, indicating that students with bad grades might have already left the university. However, we identified no impact of part-time jobs on grades ($p > 0.1$). Although study effort related to better grades, the effect was again gender-specific. The use of Facebook for university contacts and the time of adoption returned insignificant effects ($p > 0.1$).

4.3 Robustness of Results

We conduct several robustness tests. First, we check the model for multicollinearity. Models 1–3 in *Table 6* show that the models without interactions have low variance inflation factors (VIFs) with a mean VIF < 1.44 and a maximum VIF of 1.72. To further mitigate the concern of potential multicollinearity, we provide the correlation matrix in *Table 5* and estimate the models on split samples for male and female students. The results do not change substantially.

Another concern is that the high school grade, another proxy for academic performance, is also a function of Facebook use, since the subjects may already have already begun to use Facebook in high school. To check for such an impact, we exclude HSGPA as control variable in Model 5 of *Table 6*. This exclusion leads to minor changes in our results. The same holds for excluding the efforts towards studies, which we present as Model 6 of *Table 6*.

Beside the interesting gender-specific use effect, we also check for further moderating effects of age, semester, and high-school grade point average, but these analyses did not reveal further insights.

Table 5: Correlation Matrix

	1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**
1. Facebook use in general										
2. Facebook use during classes	-0.013									
3. Clustering coefficient	0.130	0.411								
4. Degree	-0.078	-0.327	-0.100							
5. High school grade point average	0.015	0.493	0.352	-0.424						
6. Semester	0.534	0.063	0.114	-0.057	0.033					
7. Age	0.000	-0.054	0.196	-0.071	0.011	0.214				
8. Part-time job	0.343	-0.117	-0.031	-0.111	-0.223	0.478	0.340			
9. Effort toward studies	0.113	-0.108	0.126	-0.140	0.147	0.109	0.112	0.029		
10. Use Facebook for university contacts	-0.224	-0.320	-0.387	0.086	-0.278	-0.316	-0.015	0.062	-0.154	
11. Adoption time in months	-0.084	0.499	0.269	-0.296	0.224	0.033	-0.151	-0.142	0.005	-0.122

Table 6: Robustness Checks and Extended Models

	Model 1 Controls Only		Model 2 FB Use in General & Controls		Model 3 Facebook Use & Controls		Model 4: FB Use & Network & Controls		Model 5: Full Model w/o High school GPA		Model 6: Full Model w/o Effort		Model 7: Full Model & All sign. Interactions	
	Coeff.	Rob. s.e.	Coeff.	Rob. s.e.	Coeff.	Rob. s.e.	Coeff.	Rob. s.e.	Coeff.	Rob. s.e.	Coeff.	Rob. s.e.	Coeff.	Rob. s.e.
FB use in general (H1)			-0.003	0.041	-0.021	0.043	-0.037	0.043	-0.046	0.044	-0.029	0.044	-0.141***	0.053
FB use during classes (H2)					0.044	0.028	0.053*	0.028	0.045	0.030	0.059**	0.027	0.049*	0.027
Clustering coefficient (H3)							-2.424*	1.246	-1.441	1.711	-2.406*	1.263	-2.397*	1.244
Degree (H4)							-0.001**	0.0005	-0.001	0.001	-0.001*	0.000	-0.001*	0.000
Degree × Gender							0.002***	0.001	0.0014**	06	0.002***	0.001	07**	0.001
FB use in general × Gender													0.202***	0.061
Gender (1: Female)	0.002	0.099	0.002	0.101	0.016	0.101	-0.577**	0.224	-0.526**	0.238	-0.557**	0.228	-2.227***	0.414
High school GPA	0.571***	0.141	0.571***	0.143	0.577***	0.137	0.616***	0.141			0.660***	0.127	0.650***	0.136
Semester	-0.075**	0.036	-0.075**	0.036	-0.091**	0.037	-0.102***	0.035	-0.094**	0.040	-0.104***	0.035	-0.113***	0.034
Age	0.061*	0.032	0.061*	0.032	0.064**	0.032	0.057*	0.032	0.140***	0.029	0.05	0.031	0.053*	0.029
Part-time job	0.003	0.005	0.003	0.005	0.002	0.005	-0.001	0.005	-0.001	0.005	-04	0.004	-003	0.005
Effort toward studies	-0.048	0.050	-0.049	0.049	-0.030	0.051	-0.046	0.047	-0.120**	0.047			-0.127**	0.054
Effort × Gender													0.211***	0.070
Use FB for university contacts	-0.033	0.025	-0.032	0.031	-0.038	0.031	-0.045	0.029	-0.031	0.032	-0.048	0.029	-0.043	0.027
Adoption time in months	0.002	0.004	0.002	04	0.003	0 4	0.002	0.004	0.005	0.004	0.002	0.004	0.001	0.004
Constant	0.585	0.616	0.598	0.606	0.434	0.630	1.368**	0.673	0.705	0.829	1.174*	0.668	2.227***	0.650
F-Value	7.881		7.112		6.364		6.249		3.549		6.406		9.090	
Prob > *F*	0		0		0		0		0		0		0	
R^2	0.344		0.344		0.362		0.419		0.276		0.413		0.493	
RMSE	0.454		0.457		0.453		0.439		0.488		0.439		0.415	
VIF Mean/Max	1.29 / 1.67		1.39 / 1.68		1.44 / 1.72		2.57 / 7.49		1.27 / 7.45		2.60 / 7.36		7.57 / 43.53	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, two-tailed significance.
FB: Facebook, RMSE: Root mean squared error, VIF: Variance inflation factor, GPA: Grade point average, Rob. s.e.: Robust standard errors.
Notes: The dependent variable is academic performance, measured by the weighted average of grades at the university level.

5 Summary, Implications, and Limitations

In this article we empirically analyze the impact of Facebook activities on academic performance. Unlike previous studies, we use multiple data sources (we measure perceptions by a survey, network positions by actual Facebook connections, and grades by the university registrar) and focus on German instead of U.S. students. Facebook activities during class relate negatively to academic performance for both genders. This finding is also supported by students' own average response (5.1 out of 7 (7=totally agree)) to the question: "My ability to study suffers if I simultaneously use Facebook."

In line with previous research that examines the impact of gender-specific networking behavior on career progress, we observe a gender-specific effect of close friendships on academic performance. The number of contacts relates positively to academic performance for men but negatively for women. According to social role theory, gender differences in behavior occur because men and women usually have different social roles (Eagly (1987)); behavioral difference such as gender-specific communication styles result from role-related expectations for women and men (Hall and Briton (1993)). In a traditionally female role, women tend to exhibit expressive, social-emotional behavior, and men performing stereotypical male roles behave in non-emotional, instrumental ways (Athenstaedt, Haas, and Schwab (2004)). Thus, instrumental, task- and goal-oriented approaches are often associated with men, but a communal approach oriented more toward social relationships is associated with women (Iacobucci and Ostrom (1993)).

In the context of our study, this association could imply that men, on average, use platforms such as Facebook to gather valuable information from their peers, but women may invest time on Facebook to cultivate relationships, which reduces the time available for their academic studies. However, this conclusion is speculative. Further research should examine gender-specific communication behavior in social media more closely to explain these differences.

A limitation of this study, which it shares with previous studies of the impact of Facebook use on academic performance (Junco (2012)), is that we observe only correlations; we do not provide evidence of causality. Our cross-sectional data make it difficult to separate the effect of students' use of Facebook from other effects, such as social contagion, homophily, and exogenous influences. Social contagion describes how behavior is transmitted in social networks, which also involves how interpersonal communications affect sales (e.g., Hinz et al. (2011)). Homophily describes the tendency of people to associate and bond with similar others. For example, young people stick together, obese people stick together, and smokers prefer to hang out with other smokers. Exogenous influences describe other variables that could influence behavior, including exposure to similar advertising messages or friends.

Although we observe many variables, we cannot rule out the possibility that other (unobserved) variables might be correlated with our treatment. We also lack good control variables (Van den Bulte and Lilien (2001); Hinz, Schulze, and Takac (2013)) or instrumental variables (Gaviria and Raphael (2001)). Thus, we can make claims about relations but not about causal effects, even though the relations are in line with the expectations stated by our hypotheses. Most notably, we cannot provide evidence that halting Facebook use during classes would necessarily improve academic performance; it could be that students with weaker academic performance self-select into the group of students who use Facebook during class. Still, the result is in line with our own and colleagues' findings.

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