The Social Structuration of Six Major Social Media Platforms in the United Kingdom: Facebook, LinkedIn, Twitter, Instagram, Google+ and Pinterest

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ABSTRACT

Sociological studies on the Internet have often examined digital inequalities. These studies show how Internet access, skills, uses and outcomes vary between different population segments. However, we know more about social inequalities in general Internet use than in social media use. Especially, we lack differentiated statistical evidence of the social profiles of distinct social media platforms. To address this issue, we use a large survey data set in the United Kingdom and investigate the social structuration of six major social media platforms. We find that age and socio-economic status are driving forces of several – but not all – of these platforms. Aggregating platform adoption into a general measure of social media use blurs some of the subtleties of more fine-grained indicators, namely platform uses and specific activities, such as status updating and commenting.

Categories and Subject Descriptors

• Human-centered computing~Collaborative and social computing • Human-centered computing~Social networks • Human-centered computing~Social media • Human-centered computing~Social content sharing

General Terms

Economics, Human Factors, Theory,

Keywords

social media, digital divide, digital inequality, Internet use, Facebook, Twitter, LinkedIn, Pinterest, Google+, Instagram

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1. INTRODUCTION

Social media are becoming increasingly ubiquitous. As of mid-2015, Facebook boasts 1.44 billion monthly users. More than half of all Americans (58%) have a profile on the platform [11].

Also in less technologically saturated countries, such as India and Indonesia, the social network site enjoys huge popularity with tens of millions of users. LinkedIn claims 364 million users worldwide and Twitter 236 million. However, the fastest growing social media site is Instagram with more than 300 million users – a staggering growth of 100 million within less than a year. Similar numbers are reported by Google+. Finally, Pinterest is the smallest of the social media platforms considered in this article with an estimated reach of 73 million users.

Given the massive adoption of social media within the last five to ten years, it is not surprising that researchers are increasingly investigating them from various perspectives [40]. In fact, we see an explosion of studies on Facebook and Twitter after 2006, the year Twitter was founded. Figure 1 shows the development of published articles in the Web of Science database with "Facebook," "Twitter," and "LinkedIn" in the title[1]. It reveals that the lion's share of studies are published about Facebook and Twitter. The other social media platforms have received less attention. LinkedIn, for example, has only 63 articles in the same time period and even less is published on Instagram, Pinterest and Google+.

Insert Figure 1 here

Wilson et al. [40] were the first to systematically assess the literature on one specific social media platform: Facebook. They found that the studies cluster in five topical areas: privacy, identity, motivations for using Facebook, social capital/social interactions, and descriptive analyses of Facebook use. In this contribution, we focus on the last cluster. Despite a range of studies in that area, few have investigated Facebook – and social media more generally – using a digital divide lens. The few studies that have, often used limited, non-representative survey samples, such as students [15] or employees of a tech company [1]. Consequently, Wilson et al. [40] call for more in-depth analyses across demographic groups and for country comparisons. "Such findings would provide valuable contextual information

[1] Choosing a less 'conservative' and more encompassing database, such as Google Scholar, results in an even more dramatic rise in the last couple of years.

about Facebook users in general and may also help explain some specific research findings." [40, p. 208]

Thanks to in-house data teams we know a lot about social media users once they are on a platform; for example their Facebook social networks, friends and families [2, 9]. However, less is known about who participates in individual platforms in the first place and what the social profiles of users and driving factors across a wide range of citizens beyond tech savvy users are. And even less empirical evidence is available on social media use across individual platforms, for example how users combine them into repertoires. In a systematic review of the social network site (SNS) literature in six major communication and Internet journals [42], the 84 articles investigated clustered in four topical areas (impression management, networks, privacy, and the bridging of online and offline networks). None of these areas concern digital inequalities in platform adoption. Hence, the topic of digital divides in social media use is severely under-represented in the literature.

Pearce [25] makes some suggestions to improve the study of social media adoption, such as using meaningful categories of use, including activities, and being aware of the fact that counts are notoriously inaccurate. She calls for collaboration with government, the media and other non-academic actors to better understand social media use.

In this contribution, we address some of these research gaps and problems with a large survey data set representative of the UK population. The data set includes questions on a wide range of Internet attitudes and uses and covers most of today's major social media platforms. Thus, we can tackle the question of social media use across individual platforms and investigate a range of antecedent conditions commonly not considered in descriptive survey studies (e.g., [11]), such as the primary device of Internet use (mobile vs. stationary), privacy concerns, self-efficacy and trust. In the tradition of digital inequality research, we aim to show how each platform has a unique social profile. Moreover, we provide evidence that social media are by no means evenly spread in society, especially when it comes to specific uses.

To do so, we proceed in three steps. First, we use logistic regression to identify the user profiles of six major social media platforms: Facebook, LinkedIn, Twitter, Instagram, Google+ and Pinterest. Second, we investigate cross-platform uses by building a composite index of social media use as the sum of individual platforms used. Linear regression is used to detect the social structuration of general social media use in the UK. Third and finally, we go beyond simple yes and no categorizations and look at what people actually do on social media platforms. To do so, we investigate the social structuration of specific social media uses (e.g., status updating, uploading photos, commenting and changing privacy settings) and show more fine-grained divides, following Pearce's [25] call to study activities instead of simple adoption. Before the empirical analyses, we briefly summarize previous research on the topic of divides in social media use. After the results and their discussion, we conclude with a summary of the findings, implications and limitations of our approach.

2. LITERATURE REVIEW

2.1 Social Media Use: What Do We Know?

One of the first and most cited studies to investigate the use of different social media platforms is Hargittai's [11] work on US college students. With a large sample of young adults, she showed how four social media platforms – Facebook, MySpace, Xanga and Friendster – differ in their social profile. Especially, some (parental) education and race/ethnicity effects are noteworthy: students from educated backgrounds disproportionally use Facebook, whereas the opposite is true for MySpace. Here, students with parents who have less than a high school degree show the largest percentage of adoption. In terms of race, the percentage of white and Asian-American Facebook users is significantly higher than that of Hispanic users. By contrast, the latter adopt MySpace to significantly higher proportions. Both Xanga and Friendster cater most to Asian-American students and both are not strongly differentiated in terms of education and gender.

The study reminds us how quickly social media changes [19]: Three out of the four platforms have become largely irrelevant and the fourth one is now the dominant player. In the meantime, however, other social media platforms have enjoyed massive adoption, especially LinkedIn, Twitter and Instagram. The most recent and comprehensive overview of US social media platform use comes from a Pew study [11]. According to these data, 58% of American adults are on Facebook, 23% on LinkedIn, 22% on Pinterest, 21% on Instagram and 19% on Twitter. In other countries, the absolute numbers are lower and harder to get. In the UK, for example, in December 2013, 33 million people are reported to use Facebook monthly or more, around half of the population [13].

Next to the scientific studies, anecdotal evidence from corporate studies or the social media providers themselves floats around online and in popular media, covering basic demographic trends. These analyses reveal, for example, that Pinterest is more likely to be used by females [39], Google+ by males [22] and Instagram has a disproportionately young, trendy and urban user base [33]. In contrast to the scientific studies, such popular media coverage often lacks the methodological transparency necessary to evaluate the results. It is unclear which sampling approach was used, where the data comes from, and how adoption and use are operationalized.

Again, the Pew data are the most recent and reliable source on the social structuration of major social media platforms across different services in the US. They reveal that income matters more for some platforms (Facebook, Pinterest) than for others (Twitter, Instagram, Tumblr) and imply that it is important to differentiate individual platforms when looking at social media adoption. Or in other words, "[…] disaggregating which specific site one is researching is important, because people do not randomly select into their uses, and aggregate analyses of SNS use may make it difficult to identify important trends" [23, p. 277].

However, the Pew studies are largely descriptive and do not look at multivariate antecedent conditions. Especially, they neglect a range of antecedents deemed important in previous research, such as Internet skills [37], self-efficacy [18] and attitudes [10]. In the next section, we proceed to enrich the basic coverage of demographic antecedents with a set of cognitive and attitudinal predictors.

2.2 Research Models

To investigate the user base of social media platforms more holistically, we use the following predictors: age, gender, income, education, marital status, number of children in the household, self-efficacy, skills, mobile vs. non-mobile Internet use, experience, privacy concerns and trust in Internet providers. We briefly describe the rationale for including each of these variables.

Age, gender, income and education are commonly used variables in digital inequalities research. Age is a strong predictor across a wide range of Internet uses, especially content-related uses via social media. In general, younger users are more likely to use participatory media, especially for non-political purposes – a finding that is robust across many countries [5, 10, 17, 18, 37]. Thus, we expect age to be a strong and significant predictor across all platforms.

Gender has a less obvious influence. While some platforms are strongly "gendered" – such as Pinterest and Instagram – others are used equally by men and women, e.g., Twitter and LinkedIn [11]. Among individuals living in the US and Canada, females adopt social media to a higher degree than men [12, 14]. However, differences in the gendered adoption of platforms show the need to disaggregate.

Income and education are markers of socio-economic status (SES). SES has proven to be an important predictor for general Internet use but to a lesser degree for social media use and content production ([5] for the discussion). However, studies of participation and social media divides have mostly looked at overall social media/SNS [12], aggregated indices (such as political content, skilled content, and social and entertainment content [5]), or individual activities [31]. Research has not systematically distinguished and disaggregated platforms, so that we have little knowledge how they differ in terms of the users' SES. Still, given previous research, we would assume that SES has a positive influence on social media platform adoption, especially when it comes to newer platforms, such as Pinterest and Instagram.

Although race might be an important predictor of social media use, we do not include it in our analysis because the data set consists largely of white UK residents. Other ethnicity categories are not represented in sufficient number in the data to obtain meaningful results (e.g., only 26 respondents in the data set have an African background and only three respondents a Chinese background). We tested the first regression with race as an independent variable included but none of the effects were significant.

Individuals' life circumstances might play a role in the adoption of social media services. Previous research on general Internet access has shown that the household status can matter, so that, for example, single households in Germany are significantly less likely to use the Internet than those in shared households, and those with a child/children aged 12-24 are more likely to use the Internet than those without children [20]. We include marital status and number of children in the household as two such variables. None of the platforms considered in this study is specifically targeted at specific groups in terms of family situation and marital status (e.g., dating platforms should be applications where marital status matters a lot[2]). In addition, previous quantitative research on social media has largely excluded such information so that we cannot make reliable predictions in terms of the effects.

The device primarily used to access the Internet (mobile vs. non-mobile) might also affect which platforms users adopt [26]. Some social media services address a mobile audience (Instagram, Twitter), whereas others (Facebook, LinkedIn) are suited for both desktop and mobile use due to their multitude of functionalities. We propose that Instagram, Pinterest, and Twitter are especially mobile-friendly, while for Facebook, LinkedIn, and Google+ the device should not have an influence.

We include experience mainly as a control variable and think that self-efficacy and (self-rated) skills should be more powerful explanatory constructs. Previous research has shown that both skills and self-efficacy have a strong and positive impact on general Internet use [37] but also social media use and participatory Internet uses (e.g., [10, 16]).

Finally, we include two attitudinal variables with privacy concerns and trust. Both have been important as research fields on their own in information systems and new media research [4, 34]. However, empirical results have often lagged behind the expectations. This is especially true for privacy concerns, where in many cases no significant relationship could be established with user behavior [35], which leads to a so-called privacy paradox [3]. Trust has been investigated in the context of online-shopping and e-business, where financial transactions are involved, but not so much in more hedonic contexts [36] like social media. We expect both privacy concerns and trust to have little influence on actual platform adoption. If there are effects, they should be weak and positive in the case of trust but negative in the case of privacy concerns.

With these, we should have a relatively encompassing set of explanatory variables. One limitation of the data set is that it lacks personality and psychological characteristics. A branch of previous research has investigated how personality characteristics affect social media use, especially Facebook ([41] for an overview on the literature). They found that extraversion has a positive effect [29, 30], while conscientiousness has a negative one [30]. Next to extraversion, narcissism is an important positive predictor [8, 21]. Overall, however, the personality traits have in many cases only a weak – if at all significant – effects on social media use [29]. Given that our study is more of a sociological than psychological investigation, we think that neglecting personality characteristics does not pose a serious threat to the validity of the results.

3. METHODS

3.1 Data

The Oxford Internet Surveys (OxIS) collect data on British Internet users and non-users. Conducted biennially since 2003, the surveys are nationally representative random samples of more than 2,000 individuals aged 14 and older in England, Scotland,

[2] We have one item on the adoption of dating services and ran the same logistic regression as we did for the six social media platforms. It turned out that marital status and self-efficacy were the only significant predictors. As can be expected, single and divorced people are significantly more likely to use such services than married and widowed people as well as those living together with a partner (without being married).

and Wales. Interviews are conducted face-to-face by an independent survey research company. The response rate for 2013 was 51%. The analyses below are based on between 860 and 1,052 social media users out of the full 2013 sample of 2,053 respondents[3].

In our sub-population, 51% are male and 49% female, the average age is 45.5 years (with a standard deviation of 16.7 years). The modal category of education (highest degree achieved) is "secondary school or equivalent" with 40% of respondents and the next most frequent category "university or equivalent" with 30% of respondents. Income shows a right-skewed distribution, with the average value being 2.56, falling in the category "12,500-20,000." The numbers show social media users are somewhat younger, better educated, with higher incomes than the British population.

3.2 Measures

The questionnaire addresses the participants' Internet use and includes a broad range of attitudinal variables, such as trust and privacy concerns. The dependent variable for the first regression consists of six items that assess the adoption of the six social media services in question. The question wording was: "Do you use any of the following?" The individual platforms were then read out individually and the respondents could answer with "Yes" or "No." We measured income as yearly household income before taxes in categories, ranging from "up to 12,500" to "70,000-80,0000." Marital status was measured with five categories: "single", "living with partner", "married", "divorced" and "widowed." The number of children in the household was assessed directly. We measured the Internet device with a categorical variable with the following values: "mostly mobile," "mostly something else," "both equally" and "do not use mobile Internet." Skills were assessed with the item: "How would you rate your ability to use the Internet". The answers ranged from "bad" (1) to "excellent" (5). We used a composite index of six items for self-efficacy[4]. The scale has a Cronbach's Alpha of 0.890. Privacy concerns and trust were both assessed with one item each: "People should be concerned about protection of credit card details when they are using new technologies" (privacy concerns) and "How much trust do you have in the people providing Internet services?" (trust). Finally, experience was measured with one item: "About how long have you been going online?" The range is from "one month" (up to one year in months and then in years) to "15 years or more."

For the second question, we aggregated the individual adoption of platforms into a composite index as the dependent variable. The scores can range from "0" (not using any social media platform at all) to "6" (using all six platforms considered). Respondents use on average 1.4 platforms, with a standard deviation of 1.3, a minimum value of "0" and a maximum value of "6."

Finally, the dependent variables for specific social media uses covered a range of individual uses, such as status updating, commenting and posting photos. Table 3 on the last page shows the specific activities considered for this study. Respondents could answer on a six-point frequency scale with the following values: "0 – never," "1 – less than monthly," "2 – monthly," "3 – weekly," "4 – daily," "5 – several times a day."

3.3 Method

We relied on logistic and linear regression to address the research questions. The statistical analysis was carried out with Stata 13.1 and we accounted for the clustered sampling approach by using the "svy" command and a sample weight variable.

4. RESULTS AND DISCUSSION

4.1 Social Media Platform Use

According to the results shown in Table 1, each platform has a different demographic and social profile in the sense that for each platform different predictors matter.

Insert Table 1 here

For Facebook, age and gender are decisive, with younger and female users being more likely to adopt it. Moreover, the significant effect of mobile use – compared to non-mobile and mostly non-mobile – shows that the device matters. In other words, Facebook seems to be especially attractive to mobile users. This finding coincides with the strategy of the company, which is increasingly tailoring its services to mobile devices. Finally, self-efficacy increases the likelihood of Facebook adoption. Scoring low on self-efficacy presents a barrier to using Facebook. Interestingly (self-reported) skills turn out to not be significant, which implies that the barriers to using Facebook are cognitive rather than a lack of actual Internet skills.

The picture is different for LinkedIn, which is targeted at professional users. In contrast to Facebook, age and gender do not matter, but income does. High income citizens are significantly more likely to use LinkedIn than their lower income counterparts. In addition, we find that divorced people are significantly more likely to use LinkedIn than single people. This finding could be due to life circumstances and life course patterns. Divorce is most likely to occur when individuals are between 30 and 50 years old [24], with the peak at the age of 40-44. In this phase, citizens are also in the middle of their professional career and hence more likely to adopt LinkedIn. Similarly to Facebook, self-efficacy strongly and positively influences the use of the platform but self-reported skills do not.

Twitter, again, has a different profile of adopters. Here, age and income, but not education and gender, affect individuals' uptake. In line with Facebook, self-efficacy and the use of mobile devices

[3] The full sample includes people who do not use the Internet – non-users – and who do not use it anymore – ex-users. These were excluded from the analysis because of the questionnaire design. Questions regarding the use of social media platforms were only asked to those who indicated using the Internet. Non-users and ex-users were filtered out before. Thus, the findings only apply to the general online population in the UK but not to the general population. We could have assigned non- and ex-users a 0-value for their platform use. However, since some important independent variables, such as skills, were only assessed for Internet users (but not non- and ex-users), we decided not to include non- and ex-users.

[4] "How confident do you feel that you are able to… a) judge the reliability of online content b) remove a virus that infected your computer c) participate in a discussion online d make new friends online) e) upload photos to a website f) download and save music (MP3s)?"

have a positive impact on the adoption. Again, self-reported skills do not matter. Many older, low-income Internet users might not see the purpose of using Twitter and might find its jargon hard to penetrate (hashtags, retweets, abbreviations etc.). This perception and its usefulness only for certain interest groups (entertainment and celebrity news, career advice, marketing, news) could account for the digital divide in Twitter use and its specific demographic profile [11, 16].

The results for Pinterest have to be taken with a grain of salt because only few respondents use the platform. Furthermore, a substantial proportion does not know Pinterest exists, indicating that it seems to be the most niche player among the six services considered. Consequently, few variables significantly predict Pinterest adoption. Like for Twitter, high income and younger users are substantially more likely to have adopted it. The status of Pinterest as an emerging and new platform means that only early adopters have taken it up yet, a group that is traditionally well equipped and tech savvy [28]. The absence of a gender effect is somewhat surprising. However, we do find a skills effect with a very high odds ratio and an interesting effect for “divorced.” Pinterest, as a new, relatively unknown platform, might mostly cater to skilled Internet users. The effect of trust is also remarkable. The more users trust Internet service providers, the less likely they are to adopt Pinterest.

For Google+, we find few significant demographic effects, but again, skills matter. Like Twitter and Pinterest, Google+ requires (self-reported) Internet skills to foster adoption. Together with LinkedIn, Google+ is the only platform where experience has a significant – and negative – effect. Users with little Internet experience are most likely to adopt Google+. The service’s role as the SNS of an Internet giant that many novice Internet users may use as one of their first applications might explain this tendency.

Finally, Instagram is not influenced by income, age, gender and education. Despite having markedly higher adoption rates than Pinterest, Instagram had not reached mainstream status in the UK at the time of the survey. The high odds ratio for skills shows that Internet skills increase the likelihood of Instagram adoption. Similarly to Pinterest, Twitter and Google+, the newness of Instagram might indicate that many users have not had the time to become familiar with the rules and codes of the platform.

4.2 Overall Social Media Adoption

In a second step, we aggregated the individual platforms to investigate the general social media divide in the UK. Table 2 shows the results of the analysis. The significant predictors of social media use in the UK (measured as uses of six individual platforms) are age, income, skills, primary device of Internet access and self-efficacy. Gender, education, children and the two attitudinal variables considered (trust and privacy concerns) do not play a role. The general social media user is young, has a high household income, above average Internet skills, uses the mobile Internet a lot (and is likely familiar and skillful in using smart phones), and is endowed with a certain self-confidence or self-efficacy.

The comparison of Table 1 and Table 2 shows that by disaggregating social media use to individual platforms certain subtleties are revealed which are lost in the aggregate picture. For example, while gender and education do not matter overall, they have an influence on certain platforms, such as Facebook (both in terms of gender and some education). Similarly, age and income might be decisive overall but they are not significant predictors for several platforms. Google+ and Instagram, for example, do not seem to depend heavily on income, and LinkedIn not on age. Moreover, the disaggregation allows us to see where skills are important and where self-efficacy matters more. The older and better known platforms (Facebook, LinkedIn, Twitter) rely strongly on self-efficacy, whereas the newer ones are more influenced by (self-reported) skills. It could be that the barriers to using certain social media platforms shift from more tangible (navigational) skills to less tangible cognitive and attitudinal hurdles [38].

Table 2 Linear regression results for demographic and attitudinal predictors on use of all platforms.

Predictor	Coefficients
Age	-0.016***
Gender	0.087
Income	0.125**
Education (reference: no qualification)	
secondary	-0.008
further	0.027
higher	-0.041
Marital status (reference: single)	
married	-0.064
living together with a partner	0.040
divorced	0.338
widowed	-0.062
Children in household	-0.151
Skills	0.142*
Device of Internet use (reference: mostly mobile)	
mostly use something else	-0.488***
both equally	0.031
don't use mobile Internet	-0.851***
Experience	-0.014
Privacy concerns	-0.027
Trust in Internet providers	0.015
Self-efficacy	0.028**
R^2	0.278
N	1039

***: $p < 0.001$ **: $p < 0.01$ *: $p < 0.05$

4.3 Specific Uses

Table 3 shows the result for specific social media uses, such as status updates (a), commenting (e), sharing (f) and unliking (j).

Insert Table 3 here

We see that all demographic predictors have an influence, but the influence varies depending on the specific use in question[5]. Generally, younger users perform the activities more often than older ones, especially activities that entail content creation. Interestingly, across most uses, females tend to be more likely to carry out various social media activities. Males are never more likely to do an activity than females. Income is only relevant for posting written content and 'liking' a company. The positive effect indicates that higher income individuals score higher. Having a secondary education improves the likelihood of carrying out seven activities, but a university education is significant only for three activities that involve writing. Skills matter less than self-efficacy, which is overall the most consistent predictor and has a positive impact on every form of social media use considered. The role of privacy concerns is more pronounced for specific uses than for platform adoption and overall social media use. As expected, privacy concerns negatively influence certain forms of social media use, especially the ones that entail self-disclosure such as updating one's status or personal information, 'liking' a company or posting written content. Privacy concerns positively influence commenting and 'liking' other's content, so that users with higher levels of privacy concerns tend to comment and 'like' more than those with lower levels. We speculate that this is because these users are more aware that there may be privacy costs associated with posting text, so for them this item is more related to awareness than to concern. Finally, the role of experience is noteworthy. Both posting written content and 'liking' companies are negatively affected by Internet experience. Perhaps novice users favor these forms as a means of self-expression but the fact that Internet experience has little predictive power across all three regressions means that this variable has largely lost its usefulness. By now, the Internet has been such an important part of everyday life for the largest part of the UK that the variable shows little variance.

The explained variance (R^2) values range from .12 to .27. We are better at explaining status updates, posting pictures, commenting, and sharing/retweeting than we are at accounting for individuals' 'likes' and privacy settings. Here, additional factors – such as social network and relational characteristics – are likely to matter as well. Future research should dedicate attention to the latter and combine content characteristics with user characteristics. That way, the predictive power is likely to be increased.

Overall, the third regression with specific social media uses as the dependent variable shows again that disaggregating is useful. Following Pearce's [25] call for considering activities rather than overall adoption, we can show that the activities sometimes reveal a different picture than what we would assume from the overall adoption (Table 2). Especially striking is the consistent effect of mobile use. Anyone using a mobile phone is more likely to do any eight of the 10 activities; the exceptions are updating personal information and posting written content.

[5] For the sake of simplicity, we excluded non-significant predictors. Marital status, number of children and trust turned out to be non-significant.

5. CONCLUSION

5.1 Summary and Implications

In this article, we analyzed the user profile of six large social media platforms, of the aggregate social media user, and of specific social media uses. In addition to demographic characteristics, we included a range of antecedent conditions deemed important in the literature, such as self-efficacy, skills, privacy concerns and the device of accessing the Internet (mobile vs. non-mobile).

Each platform considered has a different profile in terms of the (non-)significant predictors. Facebook use is influenced by age and gender, but not income and education. LinkedIn adoption is affected by income, but not age, gender and education. For Twitter, age and income, but not gender and education, matter. Pinterest depends on age and income (not education and gender), while no demographic characteristics significantly predict Google+ and Instagram use. Next to demographic characteristics, a set of other predictors affect the adoption of individual platforms. In particular, skills and self-efficacy foster the uptake of social media services. Whereas self-efficacy matters for established platforms – Facebook, LinkedIn and Twitter – (self-reported) skills are important for the newer players, namely Pinterest and Instagram. Instagram is the only platform that relies both on (self-reported) skills and self-efficacy.

By aggregating the adoption of individual platforms into a composite index, we blur some of the subtleties of specific platforms, for example their uneven adoption among men and women (as is the case for Facebook). Overall, only age and income are significant demographic predictors of social media use in our sample. The younger users adopt social media services in general; which also increases further depending on the more they earn. Next to the demographic characteristics, (self-reported) skills and self-efficacy positively influence the likelihood of social media use.

Finally, our analysis showed that the profile of specific social media uses varies significantly between demographic, cognitive and attitudinal groups. Some uses can be predicted from demographic characteristics (status updates, posting pictures, commenting), while others depend little on demographics ('liking,' updating personal information, unfriending). Comparing the disaggregated picture with the aggregated version showed that education has a different role for specific uses than for general adoption. Educated users are not more likely to adopt specific social media services and social media across the board, but when it comes to specific uses, individuals with secondary and further education (but not higher education) score highest. Thus, the overall education effect is likely to be curvilinear (inverted u-shaped) rather than linear. Future research could test for quadratic effects.

Moreover, the consideration of specific uses, instead of overall adoption, guides our understanding where the demographic predictors matter most and where we would need to include additional explanatory variables. In the case of self-disclosure and online participation that is not tied to previous content (e.g., status updates, posting pictures) the individual characteristics explain a substantially higher amount of variance than for activities that are tied to previous content (e.g., 'liking' a company, unfriending).

The findings have some implications for research in new and social media. First, they indicate the need to consider fine-grained uses. Both the consideration of individual platforms and specific uses helped to see a more complete picture of the social structuration of social media. Second, they call for the inclusion of antecedents beyond demographics. This has proved helpful and substantially extended the explanatory scope of the regressions. Third, the findings show that digital inequality is still large and constantly shifting to the newest platform, service and use. While some of the established findings in digital divide research are confirmed in our study, other emergent trends partly contradict previous investigations.

5.2 Limitations and Suggestions for Future Research

Despite these contributions, this research has limitations which restrict its scope and provide points of departure for future research. Firstly, research on digital inequality in social media is only in its infancy and often lacks a strong theoretical grounding. Our study is no exception. The research could be stronger embedded in existing theories of social inequality, such as Bourdieu's capital theory [27, 32], Weber's theory of stratification [6] or the knowledge gap hypothesis [7]. We encourage future research to use such theories to systematically study social media inequality. Secondly, the analyzed data only covers one point in time. Thus, inferences across time are not possible and the issue of isolating different causal effects remains. Future research on social media divides could use panel designs to explain changes over time.

Thirdly, the data are relatively old. Social media are rapidly evolving [19]. New platforms emerge and disappear every year. At the same time, the platforms considered in this study are all still widely in use and show no sign of decreasing user numbers [11]. The only major players we did not consider are Snapchat (due to its newness) and YouTube. Future research is encouraged to compare the profile of Snapchat users with the one of older social media platforms, using as current data as possible, and also covering YouTube. Fourthly, additional types of social media use could be considered in future research. This includes uses in specific domains, such as LinkedIn endorsements or the posting of videos. Future research should apply a holistic, theory-driven concept of social media use. Finally, we had to rely on self-reported data. Such data is subject to challenges such as memory bias and social desirability. Digital inequalities research should therefore combine different data sources, including observational data.

Overall, this study contributes to the research of social media by being one of the first investigations of Internet social media divides in the UK, and – to our knowledge – the first to systematically assess with a high quality, broad sample how the profiles of different platforms differ.

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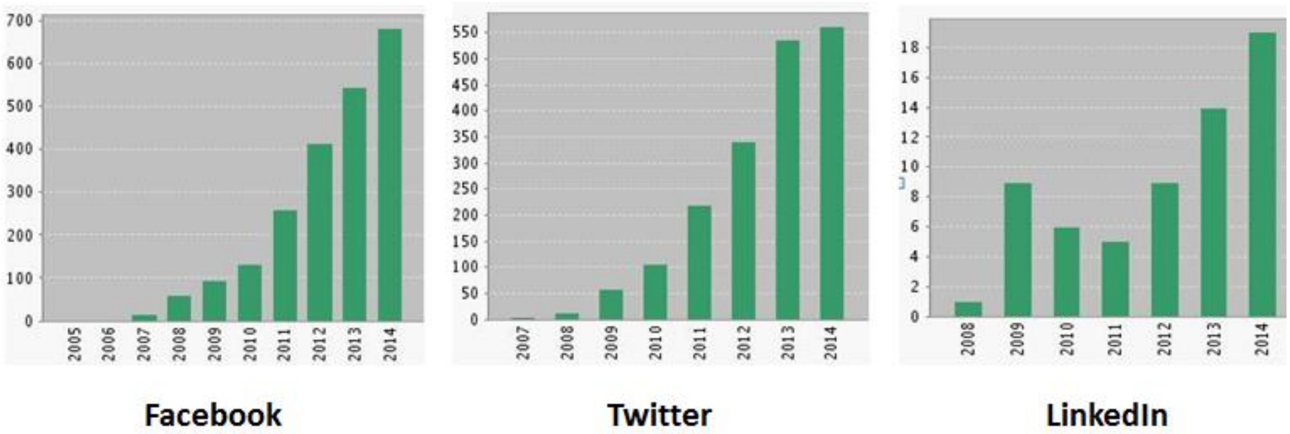

Figure 1 Articles with Facebook, Twitter and LinkedIn in title in Web of Science.

Table 1 Logistic regression odds ratios for demographic and attitudinal predictors on use of Facebook, LinkedIn, Twitter, Pinterest, Google+ and Instagram.

Predictor	Facebook	LinkedIn	Twitter	Pinterest	Google+	Instagram
Age	0.957***	0.982	0.961***	0.949*	0.996	0.978
Gender	1.892***	0.697	1.176	0.971	1.047	0.846
Income	1.130	1.177*	1.239**	1.281*	1.108	1.177
Education (reference: no qualification)						
secondary	0.913	0.585	1.217	0.361	1.008	2.753
further	1.590	0.835	0.884	2.568	0.920	1.538
higher	0.465*	1.561	0.918	0.931	1.050	2.919
Marital status (reference: single)						
married	1.513	1.163	0.989	2.752	0.674	0.663
living together with a partner	1.578	1.292	0.940	1.138	1.074	0.750
divorced	2.116	4.078**	1.515	19.175***	0.754	2.198
widowed	1.252	1.264	1.387	7.640	0.034*	1.189
Children in household	0.855	0.708	0.848	1.441	0.792	1.032
Skills	0.981	1.233	1.398	3.488**	1.217	1.371**
Location: mobile vs. non-mobile (reference: mostly mobile phone)						
mostly use something else	0.341**	0.966	0.536*	0.899	0.787	0.400*
both equally	0.898	1.131	1.151	0.635	1.067	0.792
don't use mobile Internet	0.194***	0.215*	0.136***	-	0.620	0.061**
Experience	0.967	1.109*	1.040	0.952	0.959*	0.961
Privacy concerns	0.854	1.083	1.035	0.926	0.989	0.771
Trust in Internet providers	1.185	0.863	1.261*	0.575**	0.854	1.063
Self-efficacy	1.086***	1.053**	1.063**	0.941	0.990	1.092**
N	1052	1051	1052	860	1049	1048

***: $p < 0.001$ **: $p < 0.01$ *: $p < 0.05$; “don’t use mobile Internet” was not included because it perfectly predicts non-use of Pinterest; no R^2

Table 3 Linear regression results for demographic and attitudinal predictors on specific uses.

Predictor	a	b	c	d	e	f	g	h	i	j
Age	*** -		* -		** -	** -			* -	** -
Gender (reference: male)	*** +		*** +		*** +	* +	** +			
Income				** +				* +		
Education (reference: no qualification)										
secondary	** +			** +	*** +	*** +	* +	** +		
further				* +	* +	* +				
higher										
Skills	* +					** +	* +		* +	* +
Device of Internet use (reference: mostly mobile)										
mostly use something else	* -		* -		*** -	** -		* -	** -	** -
both equally										
don't use mobile Internet	*** -		*** -		*** -	** -	* -	* -	*** -	** -
Experience			* -	** -				* -		
Privacy concerns	* -	** -		* -	** +			* -	* +	
Self-efficacy	*** +	*** +	*** +	*** +	*** +	*** +	** +	*** +	* +	*** +
R^2	.27	.15	.25	.16	.27	.23	.12	.16	.17	.17
N	798	796	798	792	800	800	796	792	797	795

***: $p < 0.001$ **: $p < 0.01$ *: $p < 0.05$; + = positive effect and - = negative effect; a = status update; b = update personal information; c = post own pictures; d = post writing; e = commenting; f = sharing/retweeting; g = check or change privacy settings; h = like a company page; i = like other's content; j = unfollow or unfriend