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Social inequality in the digital transformation
Risks and potentials of mobile health technologies for social inequalities in health

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Abstract

The paper addresses the impact of digital health technologies on social inequalities in health. We set focus on mobile health technologies (mHealth) and analyse whether (a) usage of such technologies differs by educational level and (b) whether their usage moderates social inequalities in health satisfaction. We first develop a theoretical model in order to establish potential associations between social inequality, mHealth usage, health behaviour and health satisfaction. Assuming that mHealth technologies might positively affect health behaviour, they might particularly benefit groups with low health literacy and thus, have the potential to decrease the social gap in health behaviours, that was consistently reported in previous research. On the other hand, drawing on theories in the field of the digital divide, mHealth technologies might in contrast even exacerbate existing inequalities, if groups with a higher socio-economic status use them more often (2nd level digital divide) and/or particularly benefit from using them (3rd level digital divide). Using data of the Innovation Sample of the Germany Socio-Economic Panel Study (N=5,075), we find evidence for a 2nd level digital divide in mHealth usage: Among smartphone users, higher educated respondents are more likely to use health/fitness apps. However, our results do not support the existence of a 3rd level divide: There is no difference in the benefit of usage on respondents' subjective health satisfaction by educational level. Further research is needed in order to analyse the proposed associations more in depth.

Keywords: mHealth; health inequality; digital divide; health behaviour; health literacy

1. The digital transformation as a social challenge

The digitalization has become one of the largest societal transformations of the past decades. From a sociological point of view, it is particularly interesting to study the effects of this transformation on social relations, for instance with regard to existing inequalities.

Past societal transformations, such as the women's movement or the educational expansion, were shown to have substantial, long-lasting effects on previously persistent inequality patterns. Likewise, the digitalization is discussed to cause shifts with regard to its effects on inequalities, for instance on the labour market, such as the replacement of human labour with technology and hence, the loss of employment relationships subject to social security contributions or the unequal distribution of wealth growth in favour of those using modern technologies, in education, and so forth.

In this paper, we focus on health as a crucial dimension of inequality. Health inequalities refer to systematic differences in health status, health behaviour, and access to health care between different population groups: On average, the higher their socio-economic status, the longer people live and the more years they spend in good health (Marmot et al 2012). This paper deals with the question, whether and how digital technologies in the health sector affect such inequalities.

Digital technologies and health inequalities

There are three main approaches that explain health inequalities. Materialist approaches focus on inequalities in the access to health-relevant resources (e.g. Lynch 2000). Psychosocial approaches emphasize the relevance of different subjective experiences and emotions as producers of acute and chronic stress which affect physical and mental health (e.g., Siegrist & Marmot 2004). Third, cultural-behavioural approaches focus on class differences in health-related behaviour (e.g. Cockerham 2005; Weyers 2010).

Our focus in this paper is on health-related behaviour. By health-related behaviours, one refers to health promoting behaviour, such as regular physical activity, a healthy diet that includes regular consumption of fruit/vegetables, on the one hand, and to risk behaviour on the other hand, such as smoking, alcohol consumption and an unhealthy diet with a high intake of sugar and/or fats. Empirically, risky health lifestyles are strongly associated with morbidity and premature mortality (Balia & Jones 2008).

Previous research has consistently demonstrated that groups with a low socio-economic status perform less favourable behaviours with regard to most dimensions of health-promoting or, risk behaviour, respectively (e.g. Thrane 2006). For instance, in Germany, smoking rates are twice as high among the lower educated than among higher educated (Heilert & Kaul 2017). Similar patterns can be observed for heavy drinking, however only in the male population (Bloomfield et al. 2006), and a reversed pattern was shown for health promoting behaviours such as healthy diet (Darmon & Drewnowski 2015) or regular physical exercise (Gidlow et al. 2006). Recently, the Federal Ministry of Health defined the promotion of digital communication and digital healthcare applications (E-Health) as one option to improve efficiency in the health-care system: The so-called *E-Health Gesetz* came into force in 2019.

The aim of this paper is to discuss and to provide some first empirical evidence on potential effects of digital technologies on inequalities in health behaviour. Hence, we will sketch out a theoretical framework for potential assumptions on its effects on health behaviour.

Explaining inequalities in health behaviour

There is a large body of research trying to explain social differences in health behaviour. One prominent concept, that might be particularly helpful in conceptualizing the link to digital technologies, is the social-psychological concept of *health literacy*. Although not used very often in the field of health inequality research until now, the concept might actually serve as an explanation for class-specific differences in health-related behaviour.

Health literacy is defined as the ability to obtain, understand, and use health-relevant information. Health Literacy enables us to make appropriate health decisions, and as such, to perform health promoting behaviours and refrain from risk behaviours. The concept has three dimensions: Knowledge, motivation, and the capacity to act (Nöcker 2016).

Previous research indicates that health literacy is unequally distributed between the social strata: Again, the higher their socio-economic status, the more health literacy people have on average. Social groups with higher education, more income and higher status occupations seem to have more knowledge, more motivation and more competency to act in order to perform a healthy lifestyle.

For a long time, sociology has largely neglected health behaviours as a form of social acting, and therefore, as a genuinely sociological phenomenon. As such, health behaviour can be embedded in one of the most central debates in sociology, namely the continuum between agency and structure: On the one hand, health behaviour is, at least to a certain extent, an individual choice from different alternatives; however, these alternatives will always be determined by structure, such as the individual’s position in the social hierarchy (Cockerham 2005). If health literacy is considered to be both constrained by structure and at the same time, to manifest in peoples' choices, then one might think of it as a potential link between agency and structure.

We propose that digital health technologies might tackle this particular aspect: Such technologies might change the relevance of health literacy for behaviours, as they might compensate for lacking knowledge, motivation and access to competency to act of certain social groups.

Digital health technologies: mHealth

Digital Health, sometimes referred to as *eHealth*, is a relatively new and highly dynamic development that is still only little scientifically researched. Thus, several questions on its epidemiological, health economic and social scientific relevance remain open. There is no uniform definition of digital health technologies yet; throughout this paper, we will focus on health-related applications for individuals. We do not refer to any potential eHealth technology, but we restrict our theoretical argument and our empirical analyses to the subset of *mHealth*, which describes *mobile* health technologies that can be used on mobile devices (smartphones, tablets, wearables).

The availability of mobile devices is widespread by now: For instance, the proportion of 14 to 49 year olds in Germany, who own a smartphone, amounts to 95 per cent (Bitkom 2019). There are various mHealth technologies that are for free and available to everyone who owns a smartphone or tablet, such as pedometers, or fitness apps. Therefore, in this age group and geographical context, there is a quasi-universal *potential* structural access to mHealth technologies.

2. Mobile digital technologies: a compensator or driver of social inequality in health?

In light of these facts, one might expect a potential decrease of social inequalities in health behaviours as a result of mHealth technologies: If more and more people have access to mHealth, and if it is assumed that mHealth has health promoting effects on behaviours, then this might particularly benefit groups that were formerly insufficiently equipped with health literacy and thus, performed disadvantageous with regard to health behaviour. On the other hand, it is equally plausible that mHealth technologies might not reduce, but even increase existing inequalities, if usage patterns and health benefits derived from usage differed in favour of the groups that are already advantaged with regard to their health literacy and health lifestyles.

Consequently, one might propose two alternative hypotheses with regard to the potential of mHealth to affect health inequalities, each of them based on existing theories.

(1) First, it is possible that mHealth technologies decrease social inequalities in health behaviour, and ultimately, in health outcomes, because they have the potential to compensate for low health literacy. Many mHealth technologies address exactly the components that health literacy is all about: They provide their users with information on health-related topics, that might buffer social differences in the access to health-relevant information and thus, differences in health-relevant knowledge. Furthermore, they try to set incentives and thus, motivate users to follow their health-related goals, for instance with regard to regular physical activity. Thereby, the frequent usage of mHealth might compensate for intrinsic motivational differences between low- and high-SES individuals. Third, by giving practical advice on how to implement health-promoting behaviours, e.g., by regular reminders that might help establish and maintain healthy routines, or by providing shopping lists for special diets, etc., these technologies might also help compensate for lower competencies to act healthily in certain social groups.

Given that there is largely free access to a wide range of mHealth technologies, one might argue that there are equal chances of usage. This might be particularly beneficial for social groups with overall low health literacy, which has been consistently found to be related to low SES. Thus, social inequalities in health behaviours might be reduced; such equalization of behaviours might ultimately lead to a decrease in inequalities in health outcomes.

(2) On the other hand, it is equally plausible to doubt such an optimistic perspective. Drawing on the literature on the theory of diffusion by Rogers (2003) and on the digital divide (van Dijk 2005), it is likely that despite equal structural opportunities of access, social inequalities in the usage of mHealth technologies persist, and moreover, that high SES individuals even benefit more from usage. Thereby, the social gap health behaviours might even increase, instead of being weakened.

The state of the art conducted throughout the last two decades consistently reports social inequalities in technology and internet use: In general, socially advantaged groups have been found to adopt new technologies earlier and are capable to use them better for their specific purposes, resulting in a greater benefit from usage, compared to individuals coming from lower socioeconomic strata. In his research on the *Theory of Diffusion*, Rogers (1962; 2003) has described this phenomenon for the first time, and it has been applied in a wide range of subsequent studies (e.g., Krömer & Zwillich 2014; Lin & Bautista 2017; Walker and Whetton 2002). The starting point of Roger's theory was the question, which factors at the individual level lead to the adoption (adoption) or rejection (rejection) of an innovation. He showed that that people who tend to adopt innovations early are higher educated, have a higher social status, are more exposed to the mass media, and have more social contacts that promote a takeover. From that point of view, high SES groups should be more likely to adopt mHealth technologies.

Likewise, with a specific focus on the access and usage of the world wide web, the literature in the field of the so-called *digital divide* has reported substantial and persistent social differences with regard to *who* is using the internet and *for what purpose*. Since the early beginnings of this research, a large amount of literature has established three levels of the digital divide up to now. The first level of the digital divide refers to inequalities in the access of the internet. In the beginning of the 21th century, this was considered the most crucial aspect of the digital divide. Throughout the following years, access to information and communication technologies was resolved; however, inequalities persisted, as the first level of the digital divide was replaced by a second level, referring to differences in intensity and manners of actual usage across groups, despite an equalization of structural access. The third level digital divide refers to the benefits from usage (van Deursen and Helsper 2015). It was shown that low SES groups were less likely to choose contents that are tailored to their specific purposes; as a result, they benefit to a lesser extent from using the internet.

Thus, in contrast to the assumption, that mHealth might decrease health inequalities, a counter hypothesis might me formulated: The appearance of such technologies might even increase social inequalities in health behaviours, because high SES groups have a higher probability of using mHealth and probably benefit more in case of usage as compared to low SES groups.

Located within this broader framework, the paper has two specific aims. Firstly, addressing the question of a second level digital divide in mHealth usage, we investigate social inequalities in the usage of apps using the Innovation Sample of the German Socioeconomic Panel Study (SOEP). We analyse, whether the respondents' socio-economic status is associated with the usage of smartphone applications. Secondly, addressing the third level digital divide, we conduct an explorative analysis of benefits of usage of these technologies on respondents' satisfaction with health. We seek to investigate whether there are changes regarding satisfaction with health, and specifically investigate whether these outcomes vary by socio-economic status. Building on the previously formulated assumptions we test whether there is a mediating or moderating effect of the usage of fitness-apps on the effect of socio-economic status on satisfaction with health.

3. Data and operationalization

We perform a secondary data analysis on the Innovation sample of the German Socio-economic Panel Study (SOEP-IS, see Richter and Schupp 2012). The SOEP is a representative repeated survey of private households in Germany that is conducted since 1984 (Goebel et al. 2019). The so-called Innovation sample was introduced in 2009 in order to enable researchers to test new items and question batteries on a small, yet representative sample that was specially drawn for this purpose.

In the survey year 2015, the SOEP-IS included a module on smartphone usage for different purposes, one of them being "health and fitness". Additionally, information on the respondents' satisfaction with health was collected. 5,897 respondents were surveyed in 2015. As we are interested in the effect of using a fitness app (second level digital divide), we excluded respondents who did not answer the module on Smartphone usage in the SOEP IS wave 2015 (-766 respondents). Furthermore, we exclude all respondents from the sample that have a missing on one of the variables that we are using in our analyses (-56 respondents, 1,1% of sample). 5,075 respondents remain for the final analyses.

In the first step we analyse the association between respondents' education and mHealth usage. We measure the assumed effect of education on regularly using fitness-apps and compare the social selectivity of using fitness-apps to the social selectivity of using other forms of apps, like weather-apps etc. This allows us to compare the specific second digital divide in mHealth usage to a more general digital divide.

In the following we describe how we constructed the variables used in the analyses. The final coding of the variables, as well as the absolute and relative distributions are shown in table 1. Using information about the respondents' highest school certificate and their highest occupational certificate, we construct a variable that differentiates between (1) lower secondary education (No degree, *Hauptschulabschluss*), (2) medium secondary education (*Realschulabschluss* or equivalent), (3) upper secondary education (*(Fach)Abitur*), (4) tertiary education (University or university of applied science) and (5) other educational degree.

Table 1: Univariate distribution of variables, N=5,064

	Absolute	Relative
Educational degree		
Lower secondary (No degree, *Hauptschulabschluss*)	1,643	32.4
Medium secondary (*Realschulabschluss* or equivalent)	1,485	29.3
Upper secondary (*(Fach)Abitur*)	645	12.7
Tertiary (University or university of applied science)	1,016	20.0
Other	286	5.6

	5,075	100.0
Using fitness-apps		
Not regularly (less than once a week)	4,696	92.5
Regularly (at least once a week)	379	7.5
	5,075	100.0
Using any kind of apps		
Not regularly (less than once a week)	2,882	56.8
Regularly (at least once a week)	2,193	43.2
	5,075	100.0
Satisfaction with health		
Mean		6.7
Median		7.0
Std. Dev | Variance		2.19 | 4.78
Age (mean years)		52.5
Age (median years)		54.0

The usage of a fitness-app was measured using a categorical variable in the SOEP-IS. The original variable (mobnas1, SOEP-IS innovation module) differentiated between 10 different categories, ranging from using fitness-apps "never" to using them "several times a day". We recoded the original variable into a dichotomous variable which only differentiated between using fitness-apps "regularly" (=1) or "not regularly" (=0). We considered respondents to use the app "regularly" if they answered that they use fitness-apps at least once a week. To compare the specific digital divide in the usage of fitness-apps to the digital divide in using apps in general, we constructed an additional variable. Aside using fitness-apps respondents were asked whether they use finance-, learning-, office-, messenger-, navigation- or weather-apps. We used this information to construct a variable that indicates whether respondents use any of these apps "regularly" or "not regularly", respectively. The definition of regular usage was the same as for the fitness-apps.

In the second step of our analyses we address the question whether using a fitness-app is positively associated with respondents' satisfaction with health. These estimates can only serve as a first indication for whether there might be a causal effect of mHealth on health conditions for several reasons. First, although satisfaction with health is associated with the objective health condition, it is only a proxy for the objective health condition, not a direct measurement. However, self-assessments of general health have been shown to be strongly linked to objective morbidity and are good predictors of mortality, making them a valid instrument for the assessment of health (DeSalvo et al. 2006; Idler and Benyamini 1997). Second, effects of using a mHealth app might only affect health, hence, the satisfaction with health in the long run. We assume that any potential change in health that is caused by the usage of mHealth is due to changes in behaviour. However, a shortcoming of our analysis is, that we do not have information on behaviour and behaviour change. Therefore, the expected mechanism remains latent. To measure satisfaction with health, respondents in the SOEP-IS were asked how satisfied they are with their current health condition. The variable is a metric variable ranging from 0 (completely unsatisfied) to 10 (completely satisfied) with the median at 7 and the mean at 6.7.

Finally, we derived age and age² as potentially relevant control variables for the analyses. The distribution of educational certificates differs across age cohorts because of the educational expansion of the last decades, and we expect the usage of apps, as well as health behaviour to differ as well across age-cohorts. Hence, not controlling for age might bias the estimates of our main effects. We ran the analyses also controlling for other sociodemographic factors, like gender and migration background as a robustness-check. As we do not have specific expectation why not controlling for these variables might bias the main effect, and as the results remain robust when controlling for these variables, we did not include them in the final analyses.

Table 2: General and fitness-app usage in different age-cohorts, N=5,064

Age-cohort	% using any app	% using a fitness-app
17-30	81.6	18.0
31-45	66.8	13.3
46-60	45.8	5.8
61-75	17.2	1.7
Older than 75	3.3	0.7
Mean all age-cohorts	43.2	7.5

The results in table 2 indicate the importance of controlling for age in the analyses. Whereas the use of apps in general is quite common in the youngest age-cohort of the 17 to 30 years' old (81.6%) it is rather uncommon in the oldest age-cohort (3.3% of the >75 years' old). The older the respondents, the less likely they are to use apps on their smartphones in general. The same trend can be observed for using fitness-apps, although their usage is overall far less widespread. 7.5% of all respondents use fitness-apps regularly, with 18.0% of the youngest cohort doing so, but only 0.7% of the oldest cohort.

4. Results

A second digital divide in mHealth usage?

We are first addressing the question if educational background is associated with the usage of mHealth technologies, in our case fitness-apps. We present the results of linear probability models with robust standard errors.

Table 3: LPM of the effect of education on the usage of fitness-apps (1) and using Apps in general (2), N=5,075, robust standard errors, models control for age and age².

	(1) Using fitness apps	(2) Using any app
Education (Reference: lower secondary education)		
Medium sec. educ. (Mitt. Re.)	0.02* [0.01]	0.11* [0.02]
Higher sec. educ. (Abitur)	0.04* [0.01]	0.14* [0.02]
Academic degree	0.05* [0.01]	0.15* [0.02]
Other (not specified)	0.00 [0.01]	0.01 [0.03]

*Significance (two-sided): * p<0.05,*

In table 3 we present the estimates for the effect of education, controlling for age and age². We find significant and partly substantial effects for the usage of fitness apps and the usage of any kind of an app. Hence, the data support empirical findings of previous research about a 2nd digital divide along educational level. Respondents holding higher educational certificates are more likely to use apps, including mHealth apps. However, the second level digital divide for fitness apps is less pronounced than for using apps in general. Whereas respondents with medium secondary education are 11 percentage points more likely to use any app, the probability is only 2 percentage points higher for using a fitness app. Respondents with an academic degree have a 5 percentage points higher probability of using fitness apps than persons with low educational degrees, and a 3 percentage points higher probability compared to respondents with medium secondary education. The probability of using fitness apps, as well as of using any kind of an app is almost the same for persons with high secondary degrees and persons with academic degrees. Concerning the effect of education on using fitness apps (2nd digital divide) we find substantial and significant effects. However, the social gradient for using fitness app is not very articulated.

Fitness-Apps as a mediator or moderator of the effect of education on health satisfaction - a 3rd digital divide?

The analyses in the previous subchapter addressed the question whether there is a second level digital divide in the usage of mHealth technologies. We do find only small effects of education on the usage of fitness apps. If we consider mHealth technologies as potential resources that might affect social inequalities in health, there are three different possibilities:

- *mHealth use as a mediator of the effect of education:* mHealth technologies could mediate educational inequalities in health satisfaction if the usage of mHealth technologies is structured along educational certificates and mHealth technologies affect satisfaction with health.

- *mHealth use as a moderator of the effect of education:* mHealth technologies could moderate educational inequalities in health satisfaction if e.g., independent of the probability of using mHealth technologies, different educational groups might profit from the usage of such technologies to different degrees. This might be the case if people with higher educational degrees benefit more strongly than lower educated groups.

- *mHealth use as a new dimension of inequality:* mHealth technologies could form a new dimension of inequality in health satisfaction, if using mHealth technologies and profiting from usage of mHealth technologies did not differ along educational certificates, but mHealth affected health satisfaction positively.

To test these different conflicting assumptions, we estimated four different models. The estimates of these models are presented in table 4. The first model supports what we know already from previous literature: the higher the educational degree, the more satisfied respondents are with their health. The question is whether these inequalities are mediated, moderated or not affected by the usage of mHealth technologies.

For mHealth being a substantial factor that could affect existing inequalities, using mHealth technologies needs to affect the dependent variable, health satisfaction. We estimated whether this is the case and find support in the estimates presented in model 2. Respondents who use a fitness app at least once a week report substantially and significantly higher satisfaction with their health.

The results presented in model 3 contradict the assumption that mHealth mediates the effect of education on health satisfaction. The estimates of the coefficients for education are not affected if the usage of fitness apps is additionally modelled. However, we observe that the main effect of fitness apps is reduced by 8 percentage points in model 3 compared to the effect observed in model 2. This indicates that the effect of education on satisfaction with health is somehow associated with using fitness apps.

Table 4**:** LPM of the effect of education on satisfaction with health, N=5,075, robust standard errors, models control for age and age².

	dV: Subjective health condition			
Education (Reference: lower secondary education)				
Medium sec. educ. (Mitt. Re.)	0.26* [0.08]		0.26* [0.08]	0.26* [0.08]
Higher sec. educ. (Abitur)	0.54* [0.10]		0.53* [0.10]	0.53* [0.10]
Academic degree	0.76* [0.08]		0.75* [0.08]	0.76* [0.09]
Other (not specified)	0.06 [0.14]		0.06 [0.15]	0.06 [0.15]

Mediator			
Using fitness apps (Reference: less than once a week)	0.34* [0.10]	0.26* [0.10]	0.34 [0.25]
Interactions			
Fitapp*Medium sec. educ.			-0.06 [0.31]
Fitapp*Higher sec. educ.			-0.06 [0.34]
Fitapp*Academic degree			-0.18 [0.31]
Fitapp*Other (not specified)			-0.01 [0.65]

*Significance (two-sided): * p<0.05*

In which way is shown in the estimates in model 4. We additionally calculated interaction terms between education and using a fitness app to test for moderating effects. The coefficient of education is not affected by this additional parametrisation. In contrast, the main effect of using a fitness app is increased to the level it had in model 2, but is no longer significant. The loss of significance can most likely be attributed to the relatively low number of cases that used mHealth technologies in 2015 (~7.5% of the sample). Looking at the interaction effects, we find a substantial but non-significant negative effect of having an academic degree, compared to the reference category of having low secondary education. This indicates that higher educated respondents profit less from using mHealth technologies than respondents with lower educational degrees, counter to the idea of a third level digital divide in mHealth usage.

Taken together, we find evidence for a second level digital divide in mHealth usage: The higher the respondents' education, they more likely they are to use mHealth-apps on their smartphones regularly. Instead of being a significant mediator of the effect of educational inequalities on health outcomes, however, mHealth technologies seem to be a new dimension of inequality, which is however not "explaining away" educational differences in health satisfaction, but that creates a new line of inequality that operates in addition to existing inequalities.

It seems that the higher educated do not benefit to a greater extent from regular mHealth usage in terms of their satisfaction with their overall health status. Thus, a third level digital divide of mHealth usage is not existent in the data, at least not for self-assessments of health satisfaction.

5. Conclusion and outlook

In this paper we aimed to provide first evidence whether the increasing spread of digital technologies in health, so-called mHealth technologies, might affect already known inequalities in health and health satisfaction. We build our argumentation why this could be the case around the concept of health literacy which is commonly used in public health literature, but is not too prominent as a theoretical framework in sociology so far. The central assumption is that higher socio-economic strata have on average more knowledge, more motivation and more competency to act in order to perform a healthy lifestyle. As mHealth technologies, such as fitness apps, address exactly these factors by providing information about a healthy lifestyle and by motivating the user of these apps by gamification-elements, we assumed that using these apps might positively influence health and health satisfaction. We derived two conflicting assumptions how educational inequalities in health might be affected by mHealth technologies. First, if mHealth technologies fostered a healthy lifestyle, and compensated for lower health literacy, the lower educated strata might particularly profit from using them; thus, we would observe that inequalities are decreased. This would provide evidence that promoting mHealth technologies could be a strategy of addressing health-inequalities which remained stable for centuries. In contrast, if higher educated strata use these technologies more often or are more likely or profit from the usage of such technologies, as may be expected based on previous research on the digital divide, the spread of mHealth technologies could result in even more articulated inequalities in health. An additional alternative is that the effect of education on health is not affected, but mHealth technologies form an additional, new dimension of inequality.

We used SOEP-IS innovation sample data from wave 2015 to provide some first empirical evidence on the effect of mHealth on inequalities. Although this is the best data available so far, the data are far from perfect for strict causal evidence. First, five years passed since 2015 and the digitalization of the society accelerated within the last years. Hence, having a Smartphone and using Apps is far more common today than it was five years ago. This leads to a second problem: because using Apps was less common five years ago than it is today, the cases are relatively low leading to potentially lower statistical power. Hence, results might be significant in todays' data which were not significant in the data of 2015. Third, like in most secondary analyses, the variables in the dataset are not optimal for researching on causal effects. Ideally, we would have analysed effects on health behavior directly. It is very likely that we substantially underestimate the effects of mHealth usage, if we consider health outcomes, as it usually takes some time until health behaviours manifest in health outcomes. As we do not have the potential yet to look at long-term effects on health outcomes, given the short time period that such technologies have been used, a direct measure of behaviour would have been more straightforward.

Although these factors do not allow us to conduct strict causal analyses, the results provide some first evidence on the topic. Our results show a substantial and significant effect of educational level and of using a fitness app on satisfaction with health. However, we do not find strong evidence for a 2nd digital divide in the usage of mHealth technologies. Although the effect of education on using a fitness app is significant, it remains at a rather low level with academically educated respondents having a five percentage points higher probability of using fitness apps than respondent with low secondary education. Consequently, the results do not support the assumption that mHealth technologies might mediate the effect of education on health, either by decreasing or increasing the social gradient. In fact, the results strongly indicate that educational background and the usage of mHealth technologies are two separated and both influential factors that affect health satisfaction, hence, supporting the assumption that digitalization might introduce a new line of inequality.

Additionally, the data give some support for the assumption that educational groups profit to different degrees from using mHealth technologies. Respondents with an academic degree seem to profit less from using mHealth technologies than respondents with low educational degrees, contradicting the idea of a third level digital divide in favour of the higher social strata. Although these results remain insignificant, they might indicate that indeed, groups that have long been disadvantaged with regard to health literacy, might benefit most from digital technologies providing them with the adequate knowledge, incentives and competencies to perform a healthy lifestyle.

However, considering the limitations of this research, due to very low case numbers as well as indirect measures of our concepts, there is a great need for further research in this field in order to shed light on the relationship between social inequalities in health and health behaviour in light of the digital transformation.

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