The role of platform brand in the association between social media use, stress and educational attainment

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Abstract

According to the Uses and Gratifications theory and Transformation Framework, social media users are drawn to different platforms according to platform affordances and motivations for use, with potential implications for wellbeing and functional outcomes. However, most research uses *single*- or *cross*-platform data. We tested the hypothesis, therefore, that the use of different social media platforms *differentially* predicts outcomes. Using undergraduate survey data (n=3,500+) regression analyses explored associations between time spent on eight common platforms and perceived stress and GPA scores. Platforms were also rated on design features using the Transformation Framework in order to identify potential affordance-outcome links. Our hypothesis was supported: platforms showed differential patterns of association (positive and negative) with stress and GPA, with little overlap in patterns of association with the two outcome variables. These findings suggest platforms should not be treated as a homogenous phenomenon, and implicate independent mechanisms underlying social media, wellbeing and attainment links.

Keywords: social media, social network sites, mental health, wellbeing, education, stress.

Introduction

Social Media (SM) use has increased considerably over the past decade, particularly amongst late adolescents and emerging adults, who represent the greatest users of this technology (GlobalWebIndex, 2019). Whilst the majority of research into SM use in young people, has focused on the association between SM use and mental health or wellbeing, parallel research has also explored the association between SM use and functional outcomes, including academic attainment. Although these fields have remained largely independent to date, syntheses of the literatures would suggest that they are plagued by common limitations; see Doleck and Lajoie (2018) and Orben (2020) for example. First, research in both fields has tended to use reductive measures of SM engagement (e.g. hours of use) that do not capture the richness or variety of online behaviours. Second, the observed associations between SM and mental health are potentially confounded by uncontrolled user characteristics that may systematically vary with SM use and wellbeing. Third, the research has tended to focus on *single* platform or *cross*-platform data, which do not distinguish between different SM sites in terms of their appeal or potential impact (Schønning et al., 2020).

In response to these limitations, there is a growing consensus within SM-wellbeing and SM-attainment research that there is a need for a more nuanced and contextual approached that goes beyond basic dose-response models of association, to consider how the individual, the technology and the broader social context interact (Ahn, 2011; Nesi et al., 2020; Orben, 2020a). Further, we would suggest that there is merit in integrating these different streams of research, since patterns of association across different domains of wellbeing / functioning are likely to be informative as to the underlying mechanisms involved, including the potential for shared pathways and common etiological mechanisms. In this study we try to address some of these limitations, specifically, exploring the role of different SM platforms and user characteristics in the association between SM, perceived stress and educational attainment.

Platform affordances and motivations for use

According to the Uses and Gratifications theory (Kircaburun et al., 2020), SM users actively engage with SM platforms in order to satisfy needs and desires that vary between individuals. Further, the Transformation Framework (Nesi et al., 2018a, 2018b) proposes that SM platforms and technologies differ in their characteristics and design features, and critically, that these may afford different types of engagement and social interactions, presenting both novel risks and benefits to the user; see Moreno and Uhls (2019) also. Taken together, these theoretical frameworks suggest that different types of SM platforms and their associated affordances will attract different types of users that are driven by distinct motivations for use (Alhabash & Ma, 2017; Bucher & Helmond, 2018).

As a result of these differences in affordances and motivations, it is a reasonable hypothesis that different platforms will also be differentially related to indices of wellbeing and functional outcomes. Building on this perspective, Moreno and Uhls (2019) have called for a shift within the research from a focus on SM 'brand names' to an *affordances*-based approach that instead attempts to identify how different platform features impact on development and health, for good and for bad.

Social media and mental health

Research into SM and mental health, and wellbeing more generally, has explored associations between use of the technology and a range of psychological and behavioural constructs, including anxiety (Keles et al., 2019), depression (Baker & Algorta, 2016; Vidal et al., 2020), self-esteem (Saiphoo & Vahedi, 2019), perceived stress (Hampton et al., 2014), life satisfaction (Hawi & Samaha, 2017), self-harm (Biernesser et al., 2020) and suicidality (Sedgwick et al., 2019). The majority of this has, to date, adopted a ‘concern-centric’ approach (Orben et al., 2020), focusing predominantly on the putative *harmful* effects of SM use (Schønning et al., 2020). Nonetheless, research has also found associations between high levels of SM use and positive well-being, suggesting potential benefits as well as risks (Uhls et al., 2017).

Where meta-analyses and systematic reviews of the field have been undertaken these have typically reported small, but statistically significant associations between higher levels of SM use (typically more than three hours per day) and poorer mental health (Abi-Jaoude et al., 2020; Keles et al., 2019; McCrae et al., 2017; Orben, 2020b), although due to methodological limitations of the literature it has not been possible to infer a definitive direction of causality (Aalbers et al., 2019; Frison & Eggermont, 2017; Orben & Przybylski, 2019).

Some have suggested that such documented associations, whilst statistically significant, are too small to be of practical or clinical significance (Orben & Przybylski, 2019). Nonetheless, it is possible that more pronounced associations exist between SM engagement and wellbeing / mental health, but that these are dependent on moderating variables that are not consistently modelled across studies. For example, there is a relative dearth of research exploring the role of inter-individual differences in risks and resiliencies, including the potential role of even basic socioeconomic and demographic variables such as age, gender, ethnicity and socioeconomic status (Orben, 2020b). Critically for this study, the majority of research in the field to date has also drawn upon *single*-platform data (39% according to one scoping review), or else *cross*-platform data (43%), neither of which facilitate identification of potentially differential effects of platform brand (Schønning et al., 2020).

However, there are some exceptions in the literature, several of which are discussed below. For example, Wirtz et al. (2020) used an experience sample methodology to track how use of Facebook, Twitter and Instagram predicted subjective well-being across time in a sample of 77 participants (demographics not gathered). The authors reported that use of all three platforms was associated with elevated negative affect and lower subjective wellbeing, and further, provided evidence to suggest that the negative effects of SM use (for Facebook at least) are driven in large part by online social comparisons. Using a mixed methods design that included experience sampling data (n=128) as well as qualitative interviews (n=28) Bayer et al. (2016) compared interactions on Snapchat relative to Twitter and Facebook (as well as other forms of communication), and found that mood tended to be more positive following Snapchat use than it was following engagement on the other platforms.

A number of studies have instead used the statistical method of Latent Class Analysis (LCA) to address the question, a technique that facilitates the identification of classes of SM users based on factors such as use across different platforms (and/or related variables) that can then be tested for association with mental health and other outcomes. For example, in a study of 1062 18-24 year olds Ilakkuvan et al. (2019) identified five class of users: *low users*, *high (overall) users*, *professional users* (high use of LinkedIn), *creative users* (high use of Vine and Tumblr) and *mainstream users* (high use of Facebook and YouTube). Exploring how membership of these classes predicted substance use, depression and anxiety, they found that relative to *creative users*, *high (overall) users* were associated with higher odds of depression, whilst substance use showed a more complex pattern of associations across classes. Using a similar methodology Vannucci and McCauley Ohannessian (2019) identified three classes of SM users amongst 1205 11-14 year olds based on their engagement with a range of SM platforms including Facebook, Instagram, Snapcat, Tumblr and Twitter. Interestingly, relative to *low (overall) users* and *high Instagram/Snapchat users*, members of a *high (overall) use* class scored more highly on measures of depressive and panic disorder symptoms, and also exhibited other behavioural and psychosocial difficulties.

Other studies have instead asked participants more directly about the extent to which they *believe* that different SM platforms impact upon their wellbeing. For example, a survey of nearly 1,500 14-24 year olds asked participants about the extent to which they thought that 14 health and wellbeing-related factors (e.g. anxiety, loneliness, sleep quality and body image) were made better or worse by their use of various SM platforms (YouTube, Twitter, Facebook, Snapchat and Instagram) (Royal Society for Public Health, 2017). However, no data were collected on *actual* levels of SM use or mental health symptoms. Using a similar approach, Rozgonjuk et al. (2020) explored the mediating role of FOMO in the association between SM 'Use Disorders' (for different platforms) and the perceived impact of SM use on productivity (including in education or work). The authors reported significant mediating pathways for WhatsApp, Facebook, Instagram but not Snapchat. However, the concept of a 'SM Use Disorder' is highly controversial, and the study only allowed for *negative* impacts to be reported.

Thus, taken together with reviews of the field, these studies provide mixed evidence for differential effects of different SM platforms, and highlight a paucity of research in the area.

Social media and academic achievement

Relative to SM-wellbeing research, the evidence-base relating to the association between SM use and academic attainment is *much more* sparse (Doleck & Lajoie, 2018). Nonetheless, as mentioned, overlapping limitations and inconsistencies have been noted within the literature. Thus, systematic reviews and meta-analyses into the association between (general) SM use and academic attainment in adolescents have tended to report mixed findings, with studies linking higher levels of SM use to both lower and higher academic performance (Appel et al., 2020; Doleck & Lajoie, 2018) or else a small net negative effect across studies, i.e. between higher use and poorer attainment (Huang 2018; Liu, Kirschner, and Karpinski 2017; Marker, Gnambs, and Appel 2018). Interestingly, Marker, Gnambs, and Appel (2018) found that the sign of this association was inverted when studies were examined in which the technology was used specifically for academic purposes, i.e. SM use was then linked to *higher* academic achievement, once again arguing for potential risks *and* benefits of SM engagement.

Within the field, as per SM-wellbeing research, the majority of studies to date have focused on *single*-platform or *cross*-platform data**,** thereby precluding exploration of platform-specific effects (Doleck & Lajoie, 2018). For example, in a review of the literature Doleck and Lajoie (2018), in addition to highlighting a lack of research into the potential role of inter-individual or group differences in user characteristics such as age, gender, ethnicity and/or socioeconomic status, the authors reported that 74% of studies into SM use and academic attainment explored SM data based on Facebook use alone, whilst 17% focused on cross-platform use, and only *one* study included data on multiple platforms (Alwagait et al., 2015). Subsequent to publication of this review a study was published that looked at associations between Facebook, Instagram and Twitter use and social adjustment to college life, and indeed found inter-platform differences; however, the authors did not study academic *attainment* itself (Yang & Lee, 2020).

Focus of this study

Taken together, these two sets of literature suggest common limitations to the fields of SM-wellbeing and SM-attainment research, including the predominance of a decontextualised / reductionistic approach that fails to consider factors such as differences in platform affordances and user characteristics, with the vast majority of research to date having been undertaken on *single* or *cross*-platform data. Further, existing research remains inconclusive as to whether overlapping or largely separate mechanisms underpin documented associations between SM use and wellbeing and SM use and educational attainment.

In response to these limitations we describe a study that explored the role of SM in wellbeing and attainment in a single, large, emerging-adult population sample. Drawing on data from a census study of first-year undergraduate students at a Chinese University, information was available on participant demographics, socioeconomics, self-reported perceived stress and academic attainment, as well as time spent on different SM platforms. Consequently, we were able to explore the role of different SM platforms and basic user characteristics in the proposed associations with primary outcome variables (stress and academic attainment).

H1 and H2: The use of different social media platforms will be differentially associated with stress (H1) and educational attainment (H2).

According to the Uses and Gratifications theory (Kircaburun et al., 2020) and Transformation Framework (Nesi et al., 2018a, 2018b) described above, users will be drawn to different SM platforms according to platform affordances and motivations for use (Alhabash & Ma, 2017), with potential implications on outcomes. This lends itself to a clear prediction: that associations between SM use and stress (H1) and SM use and academic attainment (H2) will differ as a function of time spent on different SM platforms. In view of the dearth of studies that have explored associations with SM use across different platforms (within the same population sample), we adopted an exploratory approach, with no predictions about *which* particular SM platforms would be associated with wellbeing and education attainment. Indeed, on the basis of the Uses and Gratifications theory (Kircaburun et al., 2020) and the Transformation Framework (Nesi et al., 2018a, 2018b) as well as the wider literature (which includes many inconsistencies), we expected some platforms to be associated with *better* outcomes (e.g. lower levels of stress), and some platforms to be associated with *poorer* outcomes (e.g. lower levels of stress).

H3: Findings emerging from H1 and H2 will survive after inclusion of potential confounders, including demographic and socioeconomic variables. Whilst, as noted, SM-wellbeing and SM-attainment research has tended to treat SM users as a homogenous group, particular demographic and socioeconomic factors may be differentially linked to the risks and benefits of SM use (Doleck & Lajoie, 2018; Orben, 2020b). Further, factors such as age, gender and socioeconomic status represent potential confounders, since they have been linked to differences in educational attainment, mental health incidence and presentation, as well as SM use; see Hyde and Mezulis (2020), Voyer and Voyer (2014) and McCrae et al. (2017) for examples. Consequently, analyses underpinning hypothesis H1 and H2 were re-run with available demographic and socioeconomic variables built in as potential covariates / confounders. We predicted that whilst the core findings may be weaker following inclusion of such confounders, the main effects would persist.

Finally, we were also interested in the extent to which specific SM platforms associated with higher or lower levels of stress would be mirrored in associations with educational attainment. Thus, the existing literature is unclear as to the extent to which SM-wellbeing and SM-attainment associations are underpinned by common, overlapping or distinct etiological mechanisms, with studies rarely exploring multiple platforms and/or outcomes variables in a single population sample. Consequently, an exploratory approach was adopted, and no predictions were made as to the extent of overlap versus dissociation of findings that would emerge across outcome variables.

Materials and Methods

Data Collection and participants. A survey was conducted in late May / early June of 2020. Ethical approval was granted by the Interdisciplinary Social Science Research Centre at Zhejiang University (Project ID: 202103-01). All first-year undergraduate students at Zhejiang University in China were sent a URL link to participate in an online survey, with a brief introduction to the survey and instructions for completion. The link was distributed to individual students via their class 'groups' on the SM platform (mainly WeChat or DingTalk) of the choice of the administration staff. If students accessed the questionnaire on a mobile device they were redirected to the mobile friendly version. The questionnaire included information on demographics and socioeconomic background, educational status and attainment, SM use and self-perceived stress (see below). The survey was anonymous and students were not asked to provide personally identifiable information such as school IDs or emails.

Background information. Demographic and socioeconomic information gathered included the participants' gender, parents' highest educational attainment (both parents where available) and annual family income. With respect to educational attainment participants could respond by indicating one of the following eight categories: (i) primary school and below, (ii) junior high school, (iii) vocational high school, (iv) ordinary high school, (v) technical school, (vi) college, (vii) undergraduate, and (viii) graduate and above. However, these were compressed into three categories low (i-ii), medium (iii-vi) and high (vii-viii).

Education and attainment. In order to assess participants' educational attainment participants were asked to provide their most recent Grade Point Average (GPA) score. In addition, participants' department of study was also requested, since grading and other factors including demographics may differ between departments, potentially confounding findings.

Social Media Use. Participants were asked about their use of different SM platforms / applications. Specifically, they were asked to report -on the basis of their mobile phone records- the number of hours they'd spent on a list of Apps over the past seven days. The following eight Apps were pre-selected for inclusion according two criteria: (i) those that show the highest penetration of the Chinese market (WeChat, Weibo, QQ, Douyin, and Toutiao), and (ii) those that are deemed most popular among young adults in China (Bilibili, Zhihu, and Douban). [Note: Douyin is the Chinese version of TikTok].

Perceived Stress. Whilst perceived stress is not a direct measure of mental health *per se*, it has been proposed as a general risk factor for a wide range of psychological disorders, including anxiety and depression, as well as physical health difficulties, including cardiovascular disease and infectious diseases (Hampton et al., 2014). As such, it arguably represents an ideal construct for the study of psychological wellbeing in a general, non-clinical sample. Perceived stress was measured using the ten-item version of the Perceived Stress Scale (PSS) (Cohen, 1988). The ten-item version has higher reliability and validity than other versions of the questionnaire (Lee, 2012), with a Chinese translation of the scale having been validated (Wang et al., 2011). To check the validity of the Chinese version in our target population cognitive interviews were undertaken with two undergraduates and a number of minor modifications made to improve readability / clarity.

Analyses**.** Data were analysed using a series of linear and multinomial logistic regression analyses in which self-perceived stress (linear) and GPA (multinomial) were regressed on predictor variables in separate analyses. Basic univariate models were first run to assess for zero-order associations between key predictors and outcome variables. Predictors were then assessed for inclusion in a multistage process involving a series of forward step-wise selection analyses. Predictors were initially excluded if they did not independently improve the fit of the model according to a likelihood ratio test (LRT) ($p>0.05$) (Lewis et al., 2011). Predictors that remained were then sequentially added to the model based on the strength of their association with the outcome variable -assessed using Akaike's Information Criterion (AIC)- and retained if they significantly increased the variance explained (LRT) ($p<0.05$). These analyses were first undertaken for *person-related factors* (gender, parental education, annual household income), and separately for *SM-related factors* (i.e. time spent on each of the eight SM apps included). Finally, full multivariate models were run, with all variables included from these *person-related* and *SM-related* analyses. This allowed us to determine whether any identified associations between outcome variables and *SM-related factors* were retained after correction for the most significant *person-related factors*. Note: students' department of study was also included as a dummy variable in the multinomial GPA analysis in order to control for broad differences in grade allocation patterns across departments.

With respect to SM platform use, whilst data collected were continuous, these were transformed into ordinal data in order to allow for non-linear relationships between SM use and outcome variables (Doleck and Lajoie, 2018)**.** These categories were selected on the basis of broad cut-offs that have typically been used in previous studies and were as follows: equivalents of 0-1hr, 1-2hr, 3-5hr and 5hr+ daily use based on reported weekly total. Prior to allocation to these categories any participants who reported an equivalent of more than 12hrs daily use of *any* single platform were discarded from the data-set on the basis that they were likely reporting unreliably.

Platform classification. Whilst we made no *a priori* predictions as to what sort of SM platforms and/or affordances would be associated with positive and/or negative outcomes, we wanted to characterise the nature of the platforms studied in order to identify potential associations between functionality and outcome (*post hoc*). To this end all eight platforms were coded with respect to six key features defined by Nesi and colleagues' *transformation framework* as critical for understanding online social processes in adolescents (Nesi et al., 2018a, 2018b). These included their: (i) asynchronicity (the time lapse between sequential exchanges of information); (ii) permanence (the time-scale over which such information remains accessible), (iii) publicness (the size of the potential audience); (iv) quantifiability (whether social metrics such as likes and shares are included); (v) cue absence (whether physical cues such as vocal tone and facial expression are available); and (vi) visualness (whether sharing of visual materials such as photographs and videos are possible). Whilst Nesi and colleagues including a *seventh* feature, availability (the ease with which content can be accessed irrespective of physical location), we did not code platforms on this dimension because of its poor ability to distinguish between different SM tools / platforms, i.e. nearly *all* apps, platforms and utilities are highly accessible nowadays; see Figure 2 (Nesi et al., 2018a) (p.274). With respect to the origin of these feature dimensions, Nesi and colleagues reviewed and integrated a wide range of literature from across the fields of computer-mediated communication, media psychology, developmental psychology and organisational psychology as part of their development of the *transformation framework*, with a particular focus on "elements of social media that may have particular consequences for adolescents' experiences of peer relations online" (p.273) (Nesi et al., 2018a, 2018b).

Possible ratings for each index were low, medium, high or mixed. Platforms were coded on these dimensions by all three authors using a combination of: pre-existing knowledge / familiarity with the platforms, active exploration of the platforms, and reading of available documents describing current functionality (e.g. product reports and journalistic articles, where available). Following coding of platforms, the authors met to harmonise their findings and discuss / resolve discrepancies. At this stage, and based on the knowledge obtained from the sources described above, the researchers also categorised platforms with respect to what they felt were their dominant functions, i.e. what they are commonly used for. The following categories were agreed upon and applied through a process of discussion and emerging consensus: mainly recreation, mainly information sharing, mainly accessing news, and multiple. [Note: the decision was made *not* to include 'communication' as a function category since 'communication' is –by definition- common to all *social* media platforms].

Since, as noted, we made no *a priori* predictions as to functions or features that would be associated with positive and/or negative outcomes, we only report in the Results section summary details of how the eight platforms included were coded with respect to platform functions and the six core feature dimensions (described above). In the Discussion however, we go on to draw (tentative) *post-hoc* links between SM-wellbeing / SM-attainment correlations and associated platform functions and features in order to inform future more hypothesis –driven research. In other words, we sought to determine if platforms associated with positive and/or negative outcomes were consistently characterized by particular functions and/or high (or low) ratings on particular features.

Results

Data were available for 3670 participants, reflecting a response rate of 63.7%. Ninety-nine participants were excluded from the data for reporting >12hrs daily use on one (or more) platforms, resulting in a reduced sample of 3571 participants, and removal of 2.7% of the data. Data were complete for all variables within this sample, except for family income, for which data were not available for 644 participants (18.03%), reflecting a combination of 'don't know' responses and those who presumably did not want to provide this information. Consequently, analyses including income were undertaken on a smaller sample of 2,927 participants.

Demographic and socioeconomic information are provided in Table 1. The majority of the sample was male (60.63%). Although we did not ask participants about their age, openly available University data indicate that 99.5% of the year group from which the data were sampled were born in or after 2000, and 65.8% were born in 2001, such that the overwhelming majority of participants were 21 years of age or under. The highest frequency category with respect to mother's and father's educational level was intermediate, which corresponded to high school/college level, and the highest frequency income category was 30-50k Chinese Yuan (CYN). Finally, the median and interquartile range for participants' *total* daily SM use was 2.57 hours (IQR=1.14-4.29). This was calculated by summing hours of self-reported weekly use across all eight platforms, divided by seven.

[Table 1 near here]

Use of specific social media platforms and their association with perceived stress

Univariate linear regression analyses are presented in Supplementary Table 1 with perceived stress regressed on all predictors. These show that gender, mother's education, father's education, income and use of Weibo all predicted significant variance in stress scores. However, forward stepwise regression (run separately for demographic/

socioeconomic and SM variables) indicated that only father's education, household income and Weibo use should be retained.

When included together in a single multivariate model all retained predictors remained significant and the model explained 3.41% of variance in stress scores ($F_{(9,2917)}$=11.46, $p<0.001$, R^2=0.03) (Table 2). Thus, relative to the lowest educational level, the highest level of paternal education was associated with lower levels of stress (coefficient=-1.1, CI=-1.69—0.51, $p<0.001$). Relative to the lowest household income level (<10k CYN), household incomes of 30-50k (coefficients=-1.2, CI=-1.86—0.55, $p<0.001$) and 50-100k (coefficient=-1.79, CI=-2.48—1.09, $p<0.001$) were associated with lower levels of stress. Finally, relative to the lowest level of use (0-1hr), higher levels of Weibo use were associated with higher levels of stress, with a stepwise increase across all level of use up to the highest, i.e. 5hr+ (coefficient=2.73, CI=0.62-4.85, $p<0.05$).

[Table 2 near here]

Use of different social media platforms and their association with GPA

Univariate multinomial logistic regression analyses are presented in Supplementary Table 1 with GPA regressed on all predictors. Gender, mother's education, father's education, household income and the use of all SM platforms -except Toutiao- significantly predicted variance in GPA scores. However, forward stepwise regression of demographic/ socioeconomic predictors indicated that with respect to person-related variables only gender and household income should be retained. With respect to SM variables, forward stepwise regression indicated that all predictors except Toutiao and Douban should be retained.

When included together in a single multivariate model all predictors except gender remained significant and the model explained 6.72% of variance in GPA scores ($\chi^2_{(2,927)}$,

$p<0.001$, $R^2=0.07$) (Table 2). Note that for ease of interpretation risk ratios (RRs) associated with individual predictors reported in the text are with respect to the highest GPA category relative to the lowest only (base category). Relative to the lowest household income level (<10k), a household income of 30-50k (RR=2.2, CI=1.63-2.97, $p<0.001$) and 50-100k (RRR=4.15, CI=2.99-5.76, $p<0.001$) were associated with an increased chance of being in the intermediate or highest GPA category relative to the lowest.

With respect to individual predictors, the use of three platforms were associated with poorer academic achievement. Thus, relative to the lowest level of use (0-1hr), higher levels of Bilibili use were associated with a lower chance of being in the highest GPA bracket across all use categories between 2-3hr and 5hr+ (RR=0.38, CI=0.23-0,62, $p<0.001$). Relative to the lowest level of use, the highest level of Weibo use was associated with a lower chance of being in the highest GPA bracket (RR=0.28, CI=0.09-0.88, $p=0.03$). Finally, relative to the lowest level of use, all levels of Douyin use -other than the very highest- were associated with a reduced chance of being in the highest GPA bracket, including the 1-2hr bracket (RRR=0.38, CI=0.27-0.53, $p<0.001$).

In contrast, the use of two platforms were associated with greater academic achievement. Thus, relative to the lowest level of use (0-1hr), *intermediate* levels of WeChat use (2-3hr) were associated with a greater chance of being in the higher GPA brackets (RRR=1.94, CI=1.26-2.99, $p<0.01$). Further, relative to the lowest level of use, an intermediate level of QQ use (2-3hr) was associated with a greater chance of being in the higher GPA brackets (RRR=1.87, CI=1.15-3.06, $p=0.01$).

Classification of platforms

With respect to functionality, three platforms were coded as having multiple functions (WeChat, Weibo and QQ), two were coded as mainly recreational (Bilibili and Douyin), two were coded as being used mainly for information sharing (Weibo and Douban), and one for accessing news (Tuotiao) (Table 3). With respect to coded features, which were drawn from the transformation framework (Nesi et al., 2018a, 2018b), most platforms scored highly across many of the six feature dimensions included, with three platforms scoring maximally across *all* features (Bilibili, Weibo and Douyin). The single feature that showed the greatest variation across platforms was *visualness*, which was coded as low for information sharing platforms such as Douban and Zhihu, medium for Toutiao, high for recreational platforms such as Bilibili and Douyin, and mixed for platforms such as WeChat and QQ that are characterised by multiple functions.

[Table 3 near here]

Discussion

In terms of our stated hypotheses all three were supported. Consistent with H1 and H2, respectively, the use of specific SM platforms was differentially associated with both outcome variables, i.e. stress and academic attainment. Further, these effects survived after correction for the most predictive *person-related* factors (H3). In the context of a concern-approach to SM research and what has often been catastrophizing reporting within the media about the risks of SM to mental health, it is important to note that the amount of variance explained in outcome variables by our models, which included positive *and* negative effects for the SM-attainment model, was small. However, with respect to SM variables modelled, we only included *levels* of use rather than motivations for use or online behaviors (etc.), which might be expected to increase the level of variance explained.

With respect to the finding that the use of specific SM platforms is differentially associated with stress and academic attainment, this is consistent with both the Uses and

Gratifications theory (Kircaburun et al., 2020) and Transformation Framework (Nesi et al., 2018a, 2018b), and further, supports recent calls for a more nuanced and contextual approach to our understanding of SM use (Ahn, 2011; Nesi et al., 2020). Thus, the findings suggest that in the world of SM, not all platforms are created equal, and further, are consistent with the notion that participants are likely to engage with platforms in different ways according to inter-individual differences in motivations and platform affordances (Alhabash & Ma, 2017; Bucher & Helmond, 2018).

Although the direction of causality is not clear (more on this below), the findings open up the intuitively reasonable possibility that different SM platform are linked to different risks and benefits. Such a conclusion might also explain *some* of the inconsistencies in findings within the literature. Thus extant research in the field has typically ignored differences between platforms, either studying individual platforms in isolation or else analyzing cross-platform data that do not specify and/or model their separate effects. Because of this, it is difficult to contextualize our findings. To our knowledge no study –to date- has explored independent associations between the use of different SM platforms and academic-attainment in a single population sample (Doleck & Lajoie, 2018), and whilst some studies speak to the potential role of different platforms in mental health and well-being (a selection of which is explored in the introduction), such studies are few and far between (Schønning et al., 2020), and further, feature a number of limitations.

Beyond implicating *platform-specific* effects, the findings that we report also speak to the potential for shared versus distinct mechanisms driving SM-wellbeing and SM-attainment associations. Thus, the fact that distinct / largely non-overlapping platforms predicted stress and GPA (with the exception of Weibo) is suggestive of largely independent mechanisms. This is further reinforced by the observation that the associations between SM use and stress / attainment scores differed in form. Thus, the positive association seen between SM use and stress (which was specific to Weibo) followed a relatively linear trend, with levels of stress incrementally increasing across each time use bracket included. In contrast, for associations with GPA, whilst higher (or the highest) levels of use of particular platforms was typically associated with poorer academic achievement (Bilibili, Weibo and Douyin), where beneficial associations were seen (Zhihu and WeChat), these were linked to low or moderate levels of use, i.e. intermediate time-use categories; see the Goldilocks hypothesis (Przybylski & Weinstein, 2017). This is perhaps not surprising, since one can easily imagine how online environments that facilitate social educational processes might become problematic if used excessively, e.g. through displacement of other activities. Further, it suggests, more generally, that whilst the potential risks of SM use may emerge at higher levels of SM use, the potential benefits may be more likely to emerge at intermediate levels of use (assuming a causal link). However, this needs further exploration.

Whilst we made no *a priori* predictions as to what sort of SM platforms and/or affordances would be associated with positive and/or negative outcomes, we are able to make some tentative *post hoc* speculations, with the intention of using these to inform future more hypothesis-driven research within the field. To this end we classified all SM platforms included in this study on six key features of SM technologies proposed by Nesi and colleagues as critical to understanding their function with respect to social processes (Nesi et al., 2018a, 2018b). Using this system of classification, we found that the only SM platform to predict high levels of self-reported stress (Weibo) was rated high on *all* dimensions, suggesting that it is characterised by highly permanent, asynchronous, public, quantifiable and visual communication with a wide audience. Again, whilst highly speculative, we would suggest that these features are the most likely to trigger high levels of online social comparison, including upward social comparison, which is arguably the most robust and reliable predictor of mental health difficulties linked to SM use. Thus, high levels of online upward social comparison have been linked to poor self-esteem and symptoms of anxiety and depression across a number of studies (Kelly et al., 2018; Q.-Q. Liu et al., 2017; Schmuck et al., 2019; Tibber et al., 2020; Vogel et al., 2014, 2015; Wang et al., 2017). Further, using an experimental design, there is some evidence to suggest that the association with self-esteem (at least) may be causal, such that engaging in online upward social comparison may be actively detrimental to one's self-esteem (Vogel et al., 2014). Although the detrimental effect of upward social comparison is true of offline as well as online comparisons (Steers et al., 2014), the effect *may* be compounded on SM because of the tendency to curate one's identity online to show only positive representations of self, i.e. the social-desirability bias (Massara et al., 2012), which is facilitated by some of the platform features discussed, e.g. its asynchronicity, permanence, publicness, visualness and quantifiability (Nesi et al., 2018b, 2018a). However, it is important to note that Bilibili and Douyin were also rated high on *all* dimensions but were not associated with higher levels of stress, such that these features cannot entirely explain the pattern we report. It is interesting to note, however, that in contrast to Weibo, which was coded as having *multiple* functions, Bilibili and Douyin were coded as mainly recreational.

With respect to platforms that were associated with poorer academic achievement this included Weibo, although as noted, in contrast to its association with stress, this emerged only for the highest time-use category (5hr+). We would suggest that this is consistent with distinct mechanisms of action, e.g. displacement of educational activities at extreme levels of use. Interestingly, the other two platforms that were associated with poorer academic achievement (Bilibili and Douyin) were (as noted above) the only platforms to be categorised as *recreational* in function, arguably also consistent with a hypothesis based on potential detrimental effects that emerge through displacement of other (e.g. educational) activities at high levels of use. These platforms were also rated as high across *all* six platform features.

Finally, with respect to platforms that were associated with higher levels of educational attainment (Zhihu and WeChat), in terms of coded features, these had very little in common. Thus, Zhihu's function was classified as mainly for *information sharing (academic, society / daily life),* and scored high on all indices except for *visualness,* which was coded as low. Nonetheless, it's common use for information sharing, particularly for academic purposes (in contrast to Douban, which is associated more with sharing of *cultural* and *recreational* information) is interesting, and broadly consistent with the proposal that SM platforms that facilitate social learning processes may be linked to better educational outcomes (Ahn, 2011). In contrast, WeChat was coded as having *multiple* functions and scored in the low (or mixed) range on all features.

Taken together, these data suggest that the system of feature classification proposed by Nesi and colleagues (2018a, 2018b) *may* be useful in exploring both the potential benefits *and* risks of SM platforms, not least since all platforms associated with poorer outcomes (irrespective of outcome domain) were characterised by high feature scores across all six proposed dimensions. However, future studies need to test this and other *feature*-driven hypotheses directly across different population samples and a wider range of SM platforms. We would argue that in the context of rapidly evolving technology, dynamic shifts in patterns of use and online trends, such an approach is necessary if insights drawn from SM research is to be anything but *brand*-specific and anchored to particular (brief) moments in history.

With respect to the broader implications of this study, we are reluctant to over-interpret our findings, particularly given its cross-sectional and largely exploratory nature. Nonetheless, the finding that distinct platform features may be associated with particular benefits and risks to wellbeing and attainment (assuming this replicates and is shown to be casual in a direction running from SM use to outcome variables), points to a number of potential ‘solutions’ and/or targets for intervention. These may focus on either side of the human-technology interaction.

On the technology side, potential ‘solutions’ might involve the incorporation of ‘prosocial’ design features (Centre for Humane Technology Design, 2022). For example, with respect to our proposal that highly asynchronous, permanent, public, visual and quantifiable platforms -as defined by Nesi et al. (2018a, 2018b)- may facilitate higher levels of social comparison (and poorer wellbeing as a result), SM platforms could incorporate more options to control such features, e.g. more advanced privacy settings and an option to remove the ‘like’ feature as well as other social metrics (Grosser, 2014). However, many of these features have evolved within an ‘attention economy’ that drives design towards maximising engagement and attentional capture (Neyman, 2017), and consequently, are likely to be resistant to change.

On the human side however, we have argued elsewhere that the cultivation of more purposeful, intentional and mindful engagement with SM –as opposed to more habitual patterns of engagement (LaRose, 2010; Owen et al., 2018)- may facilitate greater access to the technology’s putative benefits and amelioration of its harms (Tibber & Silver, 2022), with the potential to bypass some of the more problematic design features of the technology. Tibber & Silver (2022) also provide some ideas for intervention, including the provision of psychoeducation and SM literacy training in educational and clinical settings (Livingstone & Helsper, 2010; Schreurs & Vandenbosch, 2021; Torrent, 2014).

With respect to the findings reported in this study, more purposeful and mindful engagement with SM may support the user to *selectively* engage with platforms that directly support their values and hence wellbeing (e.g. non-visual, closed-network platforms that cultivate a sense of connectedness and facilitate learning and sharing of educational resources). More mindful engagement will (by definition) also facilitate closer monitoring of / attention to internal and external cues (e.g. feelings of anxiety, discomfort and fatigue) that may indicate when engagement has become misaligned with the individual's values, or simply excessive. For example, the association seen between high levels of SM use and poorer educational attainment, which was evident for several platforms, might be avoided if the user were able to notice and respond to important stop cues.

In future research we will explore how such *human*- and *technology*-centred factors interact to impact on mental health / wellbeing and attainment.

With respect to the limitations of this study, one of the main issues is that SM use was based on self-report. Thus, an increasing number of studies have suggested that self-report measures of SM use may be unreliable and/or biased (Verbeij et al., n.d.). However, it is important to note that the findings we report relate to differences in associations *across* different SM platforms, such that for the effects we report to be driven by recall or reporting biases they would have to vary systematically across platforms as a function of the outcome variables in quite complex ways. In addition, GPA scores were also based on self-report, and may thus have been affected by a social-desirability bias. Future research should therefore attempt to use more objective measures of key variables, most importantly SM use itself.

Another major limitation of the study is its cross-sectional design, which precludes inferences about a direction of causality. For example, we could not distinguish whether certain types of SM platform facilitate learning and hence higher academic attainment, or instead, if individuals who do well academically are drawn more to certain types of platforms. Future studies should therefore use longitudinal and experimental designs that can begin to tease apart underlying mechanisms and directions of causality.

Conclusions: The findings reported indicate that different SM platforms were differentially associated with stress and educational attainment, and therefore suggest that SM platforms should not be treated as a homogenous group in future research. Further, they suggest that the causal mechanisms underlying the SM-wellbeing and SM-attainment associations, at least in the sample and across the range of platforms studied here, are likely to be largely independent of one another. Taken together these provide further support for recent calls within the field for a more nuanced understanding of the potential risks and benefits of SM use, which recognizes the importance of understanding how individual differences, platform affordances and online behaviors interact.

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Table 1. Demographic and socioeconomic variables. CYN=Chinese Yuan.

Variable	Level	Raw Frequency (% of total)
Gender	Female	1,406 (39.37)
	Male	2,165 (60.63)
Mother's Education	Lower	1,184 (33.16)
	Intermediate	1,460 (40.88)
	Higher	927 (25.96)
Father's Education	Lower	988 (27.67)
	Intermediate	1,370 (38.36)
	Higher	1,213 (33.97)
Income (CYN)	<10k	515 (17.59)
	10-30k	637 (21.76)
	30-50k	941 (32.15)
	50-100k	834 (28.49)
	Not available	644 (18.03)

Table 2. Regression of stress (linear regression) and Grade Point Average (multinomial regression) on demographic, socioeconomic and social media predictors. Only multivariate models are show. Note: data are not shown for Toutiao or Douban as these did not significantly predict GPA or stress in any of the models run. GPA=Grade Point Average; RR=risk ratio; Mother's Ed=mother's education level; Father's Ed=father's education level, where lower=high school education or equivalent and higher=college or higher. Significant predictors are presented in bold.

		Stress Multivariate Model		GPA Multivariate Model Intermediate to low GPA		GPA Multivariate Model High to low GPA	
Predictor	Level	Coefficient (95% CIs)	P value	RR (95% CIs)	P value	RR (95% CIs)	P value
Gender	Male	-	-	1 (0.77,1.31)	0.99	1.1 (0.85,1.43)	0.47
Father's Ed	Intermediate	-0.47 (-1.01-0.07)	0.09	-	-	-	-
	Higher	**-1.1 (-1.69--0.51)**	**<0.001**	-	-	-	-
Income	10-30k	-0.16 (-0.85-0.52)	0.64	1.32 (0.98,1.78)	0.07	1.47 (0.02,2.02)	0.02
	30-50k	**-1.2 (-1.86—0.55)**	**<0.001**	**1.57 (1.18,2.1)**	**0.002**	**2.2 (1.63,2.97)**	**<0.001**
	50-100k	**-1.79 (-2.48—1.09)**	**<0.001**	**2.16 (1.56,2.99)**	**<0.001**	**4.15 (2.99,5.76)**	**<0.001**
Bilibili	1-2hr	-	-	1.11 (0.85,1.45)	0.45	0.81 (0.62,1.06)	0.13
	2-3hr	-	-	1.08 (0.77,1.51)	0.65	**0.69 (0.49,0.97)**	**0.04**
	3-5hr	-	-	0.75 (0.49,1.15)	0.2	**0.54 (0.35,0.84)**	**<0.01**
	5hr+	-	-	0.7 (0.44,1.1)	0.13	**0.38 (0.23,0.62)**	**<0.001**
WeChat	1-2hr	-	-	1.14 (0.82,1.55)	0.41	1.27 (0.92,1.74)	0.15
	2-3hr	-	-	**1.65 (1.08,2.52)**	**0.02**	**1.94 (1.26,2.99)**	**<0.01**
	3-5hr	-	-	1.15 (0.65,2.04	0.62	1.39 (0.78,2.46)	0.26
	5hr+	-	-	1.08 (0.55,2.1)	0.83	1.56 (0.79,3.09)	0.2
Weibo	1-2hr	**0.48 (0.01-0.95)**	**<0.05**	**0.78 (0.6,1)**	**<0.05**	0.9 (0.7,1.15)	0.41
	2-3hr	**1.93 (1.07-2.79)**	**<0.001**	0.92 (0.57,1.49	0.74	1.02 (0.63,1.64)	0.94
	3-5hr	**2 (0.4-3.6)**	**<0.05**	1.2 (0.5,2.84)	0.68	1.02 (0.42,2.46)	0.97
	5hr+	**2.73 (0.62-4.85)**	**<0.05**	0.95 (0.36,2.47)	0.91	**0.28 (0.09,0.88)**	**0.03**
Zhihu	1-2hr	-	-	**1.26 (1,1.57)**	**<0.05**	**1.37 (1.09,1.71)**	**<0.01**
	2-3hr	-	-	0.92 (0.57,1.49)	0.74	1.58 (1,2.52)	0.05
	3-5hr	-	-	1.29 (0.53,3.18)	0.58	1.02 (0.4,2.59)	0.97
	5hr+	-	-	- (0,1)	0.97	- (0,1)	0.97
QQ	1-2hr	-	-	1.27 (0.82,1.96)	0.28	1.46 (0.95,2.23)	0.08
	2-3hr	-	-	1.62 (0.99,2.66)	0.06	**1.87 (1.15,3.06)**	**0.01**
	3-5hr	-	-	1.68 (0.94,2.99)	0.08	1.27 (0.71,2.29)	0.42
	5hr+	-	-	0.96 (0.53,1.74)	0.89	0.65 (0.35,1.21)	0.17
Douyin	1-2hr	-	-	**0.54 (0.39,075)**	**<0.001**	**0.38 (0.27,0.53)**	**<0.001**
	2-3hr	-	-	0.59 (0.35,1.02)	0.06	**0.33 (0.18,0.58)**	**<0.001**
	3-5hr	-	-	1.58 (0.72,3.47)	0.25	**0.22 (0.07,0.65)**	**<0.01**
	5hr+	-	-	0.88 (0.22,3.6)	0.86	0.39 (0.08,1.91)	0.24

Table 3. Classification of social media platforms used in study according to features defined by Nesi et al. (2018a, 2018b). Asyn=asynchronicity; Perm=permanence; Cue=cure absence; Quant=Quantifiability; Visual=visualness.

Platform	Function	Asyn	Perm	Public	Cue	Quant	Visual
Bilibili	Mainly recreation	High	High	High	High	High	High
WeChat	Multiple	Low	Mixed	Low	Mixed	Low	Mixed
Weibo	Multiple	High	High	High	High	High	High
Zhihu	Mainly info sharing (academic, society / daily life)	High	High	High	High	High	Low
QQ	Multiple	Low	Mixed	Optional /Mixed	Mixed	High	Mixed
Douyin	Mainly recreation	High	High	High	High	High	High
Toutiao	Mainly accessing news	High	High	High	High	High	Medium
Douban	Mainly info sharing (cultural, recreational)	High	High	High	High	High	Low

Supplementary Table 1. Univariate regression analyses for stress (linear regression) and GPA (multinomial logistic regression. GPA=Grade Point Average; RR=risk ratio; Mother's Ed=mother's education level; Father's Ed=father's education level, where lower=high school education or equivalent and higher=college or higher. Significant predictors are presented in bold.

		Stress		GPA - Intermediate to low GPA		GPA - High to low GPA	
Predictor	Level	Coefficient (95% CIs)	P value	RR (95% CIs)	P value	RR (95% CIs)	P value
Gender	Male	-0.98 (-1.38—0.58)	**<0.001**	**1.26 (1.03-1.54)**	**0.02**	**1.95 (1.61-2.36)**	**<0.001**
Mother's ed	HS/eq	**-0.57 (-1.03—0.11)**	**0.02**	**1.25 (1.01-1.54)**	**0.04**	**1.59 (1.29-1.95)**	**<0.001**
	College/higher	**-1.34 (-1.85—0.82)**	**<0.001**	**1.39 (1.08-1.79)**	**0.01**	**2.36 (1.85-3)**	**<0.001**
Father's ed	HS/eq	**-0.54 (-1.03—0.05)**	**0.03**	**1.25 (1-1.56)**	**<0.05**	**1.54 (1.23-1.91)**	**<0.001**
	College/higher	**-1.42 (-1.92—0.92)**	**<0.001**	**1.34 (1.06-1.69)**	**0.02**	**1.92 (1.53-2.42)**	**<0.001**
Income	50K~100K	-0.31 (-0.99-0.38)	0.38	1.32 (0.98-1.77)	0.07	1.46 (1.08-1.97)	0.01
	100K~200K	**-1.43 (-2.06—0.8)**	**<0.001**	**1.59 (1.2-2.1)**	**0.001**	**2.26 (1.71-3)**	**<0.001**
	200K+	**-2.14 (-2.79—1.49)**	**<0.001**	**2.15 (1.57-2.94)**	**<0.001**	**4.3 (3.16-5.86)**	**<0.001**
Bilibili	1-2hr	0.29 (-0.2-0.78)	0.25	1.27 (1-1.6)	<0.05	1.12 (0.9-1.4)	0.3
	2-3hr	0.13 (-0.48-0.74)	0.68	1.3 (0.98-1.73)	0.07	0.95 (0.72-1.26)	0.73
	3-5hr	0.26 (-0.56-1.08)	0.54	1.01 (0.7-1.47)	0.95	0.82 (0.57-1.17)	0.27
	5hr+	0.68 (-0.22-1.59)	0.14	0.88 (0.6-1.29)	0.51	**0.51 (0.34-0.75)**	**0.001**
WeChat	1-2hr	-0.1 (-0.7-0.5)	0.74	1.11 (0.85-1.45)	0.44	1.27 (0.98-1.65)	0.07
	2-3hr	0.1 (-0.42-0.83)	0.78	**1.86 (1.31-2.64)**	**0.001**	**2.28 (1.61-3.21)**	**<0.001**
	3-5hr	0.22 (-0.76-1.2)	0.66	1.42 (0.88-2.28)	0.15	**1.82 (1.15-2.87)**	**0.01**
	5hr+	-0.17 (-1.38-1.04)	0.78	1 (0.57-1.74)	1	1.27 (0.75-2.16)	0.38
Weibo	1-2hr	**0.51 (0.08-1.04)**	**0.02**	0.91 (0.74-1.12)	0.36	1.19 (0.98-1.45)	0.08
	2-3hr	**1.84 (1.04-2.65)**	**<0.001**	1.19 (0.79-1.8)	0.41	**1.69 (1.14-2.51)**	**<0.01**
	3-5hr	**1.58 (0.15-3)**	**0.03**	1.36 (0.65-2.84)	0.42	1.61 (0.79-3.29)	0.19
	5hr+	**2.04 (0.01-4.1)**	**<0.05**	1.34 (0.56-3.24)	0.51	0.61 (0.23-1.65)	0.33
Zhihu	1-2hr	-0.33 (-/074-0.09)	0.12	**1.26 (1.03-1.53)**	**0.02**	**1.4 (1.16-1.69)**	**0.001**
	2-3hr	-0.39 (-1.25-0.48)	0.38	0.88 (0.58-1.34)	0.56	1.36 (0.92-1.99)	0.12
	3-5hr	0.44 (-1.22-2.1)	0.6	1.66 (0.74-3.75)	0.22	1.33 (0.58-3.03)	0.5
	5hr+	-0.2 (-2.68-2.27)	0.87	2.02 (0.42-9.79)	0.38	3.55 (0.8-15.68)	0.1
QQ	1-2hr	-0.62 (-1.41-0.18)	0.13	1.19 (0.82-1.74)	0.35	1.03 (0.73-1.46)	0.87
	2-3hr	-0.59 (-1.46-0.28)	0.19	1.43 (0.95-2.17)	0.09	1.17 (0.79-1.73)	0.42
	3-5hr	-0.87 (-1.92-0.18)	0.1	1.45 (0.89-2.36)	0.14	0.85 (0.53-1.37)	0.52
	5hr+	-0.1 (-1.24-1.03)	0.86	0.88 (0.54-1.45)	0.62	**0.44 (0.27-0.73)**	**0.001**
Douyin	1-2hr	-0.86 (-1.91-0.19)	0.11	**0.52 (0.39-0.7)**	**<0.001**	**0.43 (0.32-0.57)**	**<0.001**
	2-3hr	**-3.62 (-6.67—0.57)**	**0.02**	**0.58 (0.36,0.93)**	**0.02**	**0.4 (0.24-0.64)**	**<0.001**
	3-5hr	2.01 (-6.33-10.36)	0.64	1.53 (0.77-3.05)	0.22	**0.24 (0.09,0.62)**	**<0.01**
	5hr+	-1.49 (-13.29-10.31)	0.81	0.77 (0.25-2.37)	0.65	0.37 (0.11,1.3)	0.12
Toutiao	1-2hr	-0.27 (-0.96-0.41)	0.44	1.07 (0.67,1.71)	0.77	0.79 (0.49,1.27)	0.33
	2-3hr	0.35 (-0.79-1.49)	0.55	0.66 (0.18,2.46)	0.53	0.64 (0.18,2.27)	0.49
	3-5hr	0.84 (-0.79-2.47)	0.31	0 (0,-)	0.99	0.43 (0.03,6.82)	0.55
	5hr+	**3.97 (1.18-6.75)**	**<0.01**	0 (0,-)	1	0 (0,-)	1
Douban	1-2hr	**0.75 (0.02-1.48)**	**0.04**	**1.63 (1.09,2.45)**	**0.02**	**2.1 (1.43,3.1)**	**<0.001**
	2-3hr	1.12 (-1.16-3.4)	0.34	0.87 (0.28,2.67)	0.81	1.27 (0.46,3.54)	0.65
	3-5hr	1.92 (-1.23-5.08)	0.23	1.27 (0.33,4.93)	0.73	0.6 (0.13,2.71)	0.51
	5hr+	2.5 (-1.97-6.96)	0.27	2.18 (0.24,19.5)	0.49	0.91 (0.08,10.01)	0.94