Internet and Social Media Use in American Adults

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Abstract

The present study examined individual differences in interactions with social media content and media consumption in American adults. Secondary data analyses were conducted using an early 2018 phone survey collected by the Pew Research Center (2018). Results showed that older age was associated with lower social media use overall, but these age-related differences varied across social media sites. That is, age-related differences were largest with respect to Snapchat and Twitter use relative to Facebook use. Male respondents also reported less frequency of social media use overall but exhibitted greater use of both Twitter and YouTube than female respondents. Examination of media consumption revealed that both age and media format are significant predictors of the volume of media consumption. Older respondents were reading more than younger respondents, and books in print were read less than those in electronic formats. A marginal interaction between age and media format suggests that the amount of media consumed increases with age more for individuals using exclusively electronic or audiobook formats than for those using exclusively print or mixed media formats.

Keywords: social media use, internet attitudes, media format, age, sex, pew research center

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Social media sites are commonly defined as an internet-based service allowing for the creation and broadcast of user-generated information (Boyd & Ellison, 2008; Kaplan & Haenlein, 2010; Obar & Wildman, 2015). Obar and Wildman (2015) emphasize the user-generated aspect of this definition, arguing that this content is the lifeblood of social media. Although that may sound hyperbolic, it logically follows that if a site is created with the express purpose of providing user-generated content, it must have user-generated content to function as intended. By way of illustration, without videos created by users, YouTube, a social media site that allows its users to upload and share videos, would fail to serve its primary purpose. Netflix, a site that allows users to only stream videos, does not require user-generated content, as it does not serve user-generated content, and, by extension is not a social media site. Beyond the functional aspects of social media sites, the user-generated focus also highlights the importance of individual differences in the user-service relationship, as users invariably have characteristics that affect how they consume and generate content.

Moreover, in an increasingly internet-based world, many new formats for media consumption have arisen. The days of reading the morning paper as the only source of world news are gone; rather, the internet provides a myriad of other media formats from which to choose. With increasing usage of digital media formats in recent years, there has been a growing interest in whether or not the format of media consumption relates to how well information is learned and retained (Delgado, Vargas, Ackerman, & Salmerón, 2018; DeZee, Durning, & Denton, 2005; Margolin, Driscoll, Toland, & Kegler, 2013). DeZee et al. (2005) found that students in their third year of a medical clerkship did not show any performance differences regardless of whether they chose to use electronic or print resources as their primary method of study. However, a meta-analysis by Delgado et al. (2018) found that paper-based reading may result in better comprehension than digital-based reading. Inconsistent findings from prior work highlights the importance of understanding individual differences in media consumption and choices to interact with media in various formats.

To explore these individual differences in how people both generate social media content and consume media in general, we conducted secondary data analyses using recent survey data collected by the Pew Research Center (2018). First, we examined how frequency of social media use might vary as a function of sex, age, and social media site. Second, we examined relationships between age and media format and how these two factors may predict the volume of media consumption.

Method

As stated above, survey data examining attitudes towards technology and use of technology and social media was collected by the Pew Research Center (2018). For the current study, we conducted a secondary data analysis looking at factors that relate to frequency of social media use, as well as factors that relate to overall media consumption.

Participants

Two thousand, two people were surveyed by telephone (75.02% cell phone; 24.98% land-line) over a period of 7 days in January of 2018. We excluded any participants who reported that they do not even occasionally use the internet or email ($n = 273$). The resulting sample comprised 1729 people (45.29% female). Ages ranged from 18 to 97 (*M* age = 48.29; *SD* age = 17.94)[1]. Concerning race, 68.48% identified as white, 12.78% identified as black, 3.64% identified as Asian, 2.95% identified as mixed race, and 12.15% refused to answer or reported being from some other race.

Materials and Procedure

Research personnel were instructed to read from a script while interviewing each participant. For land-line users, the script began as follows: "Hello, I am ________ calling on behalf of the Pew Research Center. We are conducting a telephone opinion survey about some important issues today and we would like to include your household. May I please speak with the YOUNGEST [RANDOMIZE: (MALE / FEMALE)], age 18 or older, who is

[1]Note that the descriptive statistics for age are slightly lower than reality. Ages 97 and older were recorded as simply 97 in the data.

now at home? [IF NO MALE/FEMALE, ASK: May I please speak with the YOUNGEST (FEMALE / MALE), age 18 or older, who is now at home?]"

For cell phone users, the script was slightly different: "Hello, I am ________ calling on behalf of the Pew Research Center. We are conducting a telephone opinion survey about some important issues today. I know I am calling you on a cell phone. If you would like to be reimbursed for your cell phone minutes, we will pay all eligible respondents $5 for participating in this survey. This is NOT a sales call."

Once participants passed initial screening (e.g., 18 years of age or older) and provided verbal consent to the interview, they were asked a series of questions pertaining to internet use (e.g., "How often do you use the internet?"; options ranged from 1 = "Almost Constantly" to 5 = "Less Often"), social media use (e.g., "Do you use any of the following social media sites online or on your cell phone: Twitter, Instagram, Facebook, Snapchat, YouTube, WhatsApp, Interest, and LinkedIn?"), as well as perceptions of social media's influence on the self and society (e.g., "When you add up all the advantages and disadvantages of the internet, would you say the internet has mostly been a good thing or a bad thing for society?"; options included: "Good Thing", "Bad Thing", "Some of Both", and "Don't Know"). Participants were also asked about reading habits (e.g., "During the past 12 months, how many books (print, electronic, and audio-books) did you read either all or part of the way through?") and reading format preferences (e.g., "Thinking about all of the books you have read in the past 12 months, were any of those printed books, audio-books, or E-books?"). The interview ended with a series of demographic questions assessing variables including participant sex, age, race, marital status, education, current employment status, income, and political affiliation.

Data analysis

Data was analyzed using R (Version 3.5.1; R Core Team, 2018) and the R-packages *bindrcpp* (Version 0.2.2; Müller, 2018), *car* (Version 3.0.0; Fox & Weisberg, 2011; Fox, Weisberg, & Price, 2018), *carData* (Version 3.0.1; Fox et al., 2018), *cowplot* (Version 0.9.2;

Wilke, 2018), *dplyr* (Version 0.7.7; Wickham, François, Henry, & Müller, 2018), *emmeans* (Version 1.2.1; Lenth, 2018), *forcats* (Version 0.3.0; Wickham, 2018a), *Formula* (Version 1.2.3; Zeileis & Croissant, 2010), *ggplot2* (Version 3.1.0; Wickham, 2016), *here* (Version 0.1; Müller, 2017), *Hmisc* (Version 4.1.1; Harrell Jr, Charles Dupont, & others., 2018), *jcolors* (Version 0.0.4; Huling, 2018), *lattice* (Version 0.20.35; Sarkar, 2008), *lme4* (Version 1.1.17; Bates, Mächler, Bolker, & Walker, 2015), *lmerTest* (Version 3.0.1; Kuznetsova, Brockhoff, & Christensen, 2017), *lubridate* (Version 1.7.4; Grolemund & Wickham, 2011), *magrittr* (Version 1.5; Bache & Wickham, 2014), *Matrix* (Version 1.2.14; Bates & Maechler, 2018), *pander* (Version 0.6.1; Daróczi & Tsegelskyi, 2018), *papaja* (Version 0.1.0.9842; Aust & Barth, 2018), *plotrix* (Version 3.7.1; J, 2006), *purrr* (Version 0.2.5; Henry & Wickham, 2018), *readr* (Version 1.2.1; Wickham, Hester, & Francois, 2017), *rio* (Version 0.5.10; C.-h. Chan, Chan, Leeper, & Becker, 2018), *sjstats* (Version 0.15.0; Lüdecke, 2018), *stringr* (Version 1.3.1; Wickham, 2018b), *survival* (Version 2.42.3; Terry M. Therneau & Patricia M. Grambsch, 2000), *tibble* (Version 1.4.2; Müller & Wickham, 2018), *tidyr* (Version 0.8.1; Wickham & Henry, 2018), *tidyverse* (Version 1.2.1; Wickham, 2017), and *wesanderson* (Version 0.3.6; Ram & Wickham, 2018) for all our analyses.

Results

Frequency of Social Media Use

First, we sought to examine how frequency of social media use might vary as a function of sex, age, social media site, and the interaction between these variables. Using the *lme4* package by Bates et al. (2015), we ran a comparison of seven linear mixed-effects models predicting frequency of social media use from age, social media site, sex, and the interactions among these variables. Our first model included only the random effects. Specifically, we suspected that participants may have certain response style in evaluating their frequency of social media use. We entered the subject as a random intercept to account for interdependence in the participants' ratings. Although in many cases the scenario or context (i.e., social media site) would also be entered as a random intercept, we did not wish to generalize beyond these specific sites. Our second model added gender, followed by age in our third model. The fourth model included the social media site in question. The fifth through seventh models added (1) the interaction between sex and age, (2) the interaction between sex and social media site, and (3) the interaction between age and social media site.

As shown in Table 1, we found that the addition of age, social media site, the interaction between sex and social media site, and the interaction between age and social media site all explained a significant proportion of variance in social media site usage frequency. Using the *lmerTest* package from Kuznetsova et al. (2017) to approximate degrees of freedom with Satterthwaite's method, we found that increased age is associated with lower social media use, β = -0.10, SE = .03, p = .003 (see Figure 1C). Note that Figure 1B suggests that, overall, Facebook is associated with the most social media use, followed by YouTube, Instagram, Snapchat, and Twitter. However, when accounting for age and gender, Snapchat is actually associated with greater social media use than Facebook (β = .17, SE = .04, p < .001), and Twitter is associated with lesser social media use than Facebook (β = -0.18, SE = .04, p < .001). Critically, age also interacts with the specific social media site (see Figure 1A), insofar that increased age results in even lower rates of social media use in the case of Instagram (β = -0.28, SE = .04, p < .001), Snapchat (β = -0.32, SE = .04, p < .001), Twitter (β = -0.10, SE = .04, p= .017), and YouTube (β = -0.35, SE = .05, p < .001) when compared to Facebook.

Although the model comparison did not indicate an increase in predictive ability from the introduction of participant gender, we did find that males (in comparison to females) reported less frequency of social media use when using the approximated degrees of freedom (see Figure 2C), β = -0.15, SE = .05, p = .005. Figure 2B demonstrates that when compared to Facebook, however, men exhibited a greater frequency of using Twitter (β = .09, SE = .02, p < .001) and YouTube (β = .18, SE = .03, p < .001) than women did.

A comparison of the full model with random effects to the full model without random effects revealed that the random effects explained a significant proportion of the variance in social media site use, $\chi^2(1) = 176.01$, $p < .001$. In fact, grouping ratings by participant explained 21.65% of the variance in the frequency of using a social media site. A visual inspection of model residuals suggested a slight negative skew, but no heteroscedasticity. We also quantitatively inspected the variables for potential multicollinearity within the fullest model without the interaction effects. No multicollinearity was detected (VIF = 1.01 - 1.04).

Media Consumption

We next sought to examine how media consumption may vary as a function of age as well as media format (i.e. individuals exclusively using print media, audio-books, electronic media or combinations of the three). To explore this data we used the total number of books read in the past year as an indicator of media consumption. Survey respondents who endorsed only using a single type of media format were grouped into either print, audio, or electronic as appropriate. Respondents who endorsed using more than one type of media format were grouped together into a "mixed media" bin. Next, we calculated the average number of books read, grouped by age and media format (see Figure 3A). There appear to be age differences in the number of books read as a function of media format. For example, we see that audio-book usage seems to be more prevalent among the older respondents.

To look at the relationships between the average books read in 2017, age, and media format, we ran a multiple regression predicting the average number of books read in the past year from age and media format as well as their interaction (see Figure 3B). Results showed a significant main effect of age ($F[1, 200] = 7.99$, $MSE = 270.97$, $p = .005$, $\hat{\eta}^2_p = .038$) with older adults reading more books in 2017 than younger adults. We also saw a significant main effect of media format ($F[3, 200] = 6.17$, $MSE = 270.97$, $p < .001$, $\hat{\eta}^2_p = .085$) and pairwise comparisons revealed that books in print format were read less than those in electronic ($t(48.42) = -2.10$, $p = .041$) format. We found no difference in the number of books read exclusively in a print format and the number of books read through the audio-book format ($t(34.31) = -0.17$, $p = .863$). However, we did find that more books were read using a mixed media approach than either exclusively print ($t(135.94) = -4.99$, $p < .001$) or exclusively audio-books ($t(36.64) = -2.68$, $p = .011$). Lastly, we found no difference between media consumed by individuals who reported the used mixed media sources compared to those who exclusively preferred electronic formats ($t(50.23) = -0.04$, $p = .967$, see Table 2). Finally, there was a marginal interaction effect between age and media format where changes in average books read increased with age more for individuals exclusively using electronic formats or audio-books than for individuals exclusively using print media or a mixed media approach.

Discussion

Using data collected by the Pew Research Center (2018), we examined variation in frequency of social media use and media consumption. Namely, via secondary data analyses, we assessed (1) how frequency of social media use varies across age, sex, and social media site and (2) how amount of media consumption (as indexed by number of books read) varies across media format (print, electronic, vs audio) and age.

Results revealed large individual differences in both social media use and media consumption. In the case of the former, sex predicted social media use, with females (in comparison to males) reporting higher frequency of social media use overall. Importantly, sex also interacted with social media site. Relative to Facebook, men actually reported higher frequency of Twitter and YouTube usage than did women. This result seemingly implies that women prefer to use social media platforms with an emphasis on the generation and evaluation of picture-related content.

While increased age was associated with lower social media use frequency, the strength of this relationship changed as a function of social media site. Relative to Facebook, the largest age effects were observed in the case of Instagram, Snapchat, and YouTube. In other words, older individuals were increasingly less likely to report high usage of Instagram, Snapchat, and YouTube when compared to younger adults.

It seems plausible that, at least in the case of Instagram and Snapchat (the youngest social media sites surveyed, emerging in 2010 and 2011 respectively), newer social media sites may appeal to younger users merely because older people may be late adopters and/or are less familiar with new social media platforms/internet trends. Indeed, Facebook has been around the longest of the social media sites (since 2004), and age-related differences appear to be the smallest in this case (see Figure 1A). However, this explanation is entirely speculative, so future work should aim to better identify other sources of age-related differences across social media sites. One factor deserving attention is the reason why people chose to use social media. Perhaps older adults use social media sites that more easily allow them to keep in touch with family and friends, whereas younger adults may put more emphasis on social media sites that provide more entertainment value and creative expression as a means of enhancing social status.

Age was also a significant predictor of the volume of media consumption, as indexed via average books read in the past year. Older respondents read more than younger respondents. This result is not entirely surprising, given older adults are more likely to be retired and, therefore, may have more time to read. Media format also predicted media consumption, such that books in print were read less than books in electronic formats. Electronic formats may be preferable when considering the ease and relatively cheaper cost of downloading books through the internet. Finally, we also observed a marginal interaction between age and media format, which suggested that age-related differences in the amount of media consumed are most apparent for individuals using exclusively electronic or audio-book formats than for those using exclusively print or mixed media formats. For example, use of audio-books was least likely among younger respondents but most likely among older respondents. While failing eye-sight could contribute to this effect, the fact that a similar result is obtained for electronic formats seemingly contradicts this possibility. When predicting media consumption, future work should aim to better address reasons for potential age-related differences in media format preferences.

Collectively, the results reported herein demonstrate the importance taking into account user characteristics when trying to explain how individuals consume and generate social media content. In particular, variation in age and sex are critical in explaining social media use frequency, with differing effects arising based on the social media site in question. Age also accounted for significant variation in media consumption, which marginally interacted with media format preferences. Future work should aim to not only better explain these interactive effects but to also assess other user characteristics, such as aspects of one's personality.

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Table 1

Log likelihood comparison of linear mixed-effects models predicting social network site use from sex, age, and specific social network site.

	K	χ^2 df	Loglik.	χ^2	p
Null	3		-6857.08		
Sex	4	1	-6856.28	1.61	.205
Age	5	1	-6775.08	162.39	<.001
SNS	9	4	-6620.63	308.91	<.001
Sex X Age	10	1	-6620.27	0.72	.396
Sex X SNS	14	4	-6591.10	58.32	<.001
Age X SNS	18	4	-6532.52	117.18	<.001

Note. Participant $N = 1541$; Social Network Site $N = 5$. Null model includes only the random intercept. SNS = social network site. X indicates an interaction.

Table 2

Main effects of age and media format predicting the average number of books read in 2018.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
age	1	2,165.24	2,165.24	7.99	0.01
book_format	3	5,012.82	1,670.94	6.17	0.00
age:book_format	3	2,124.53	708.18	2.61	0.05
Residuals	200	54,193.42	270.97	NA	NA

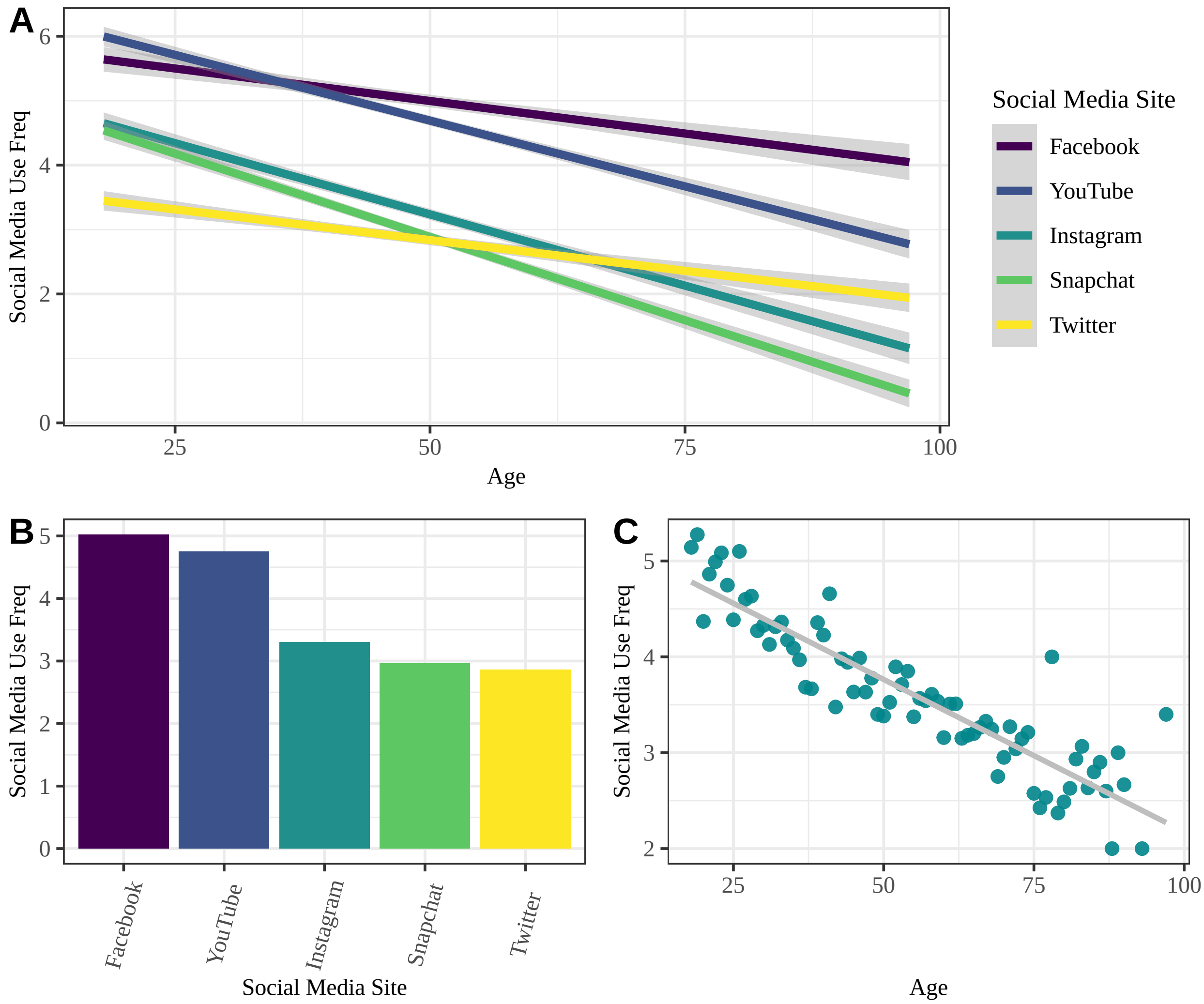

Figure 1. Frequency of social media use as a function of (a) the interaction between age and social media site, (b) social media site alone, and (c) age alone.

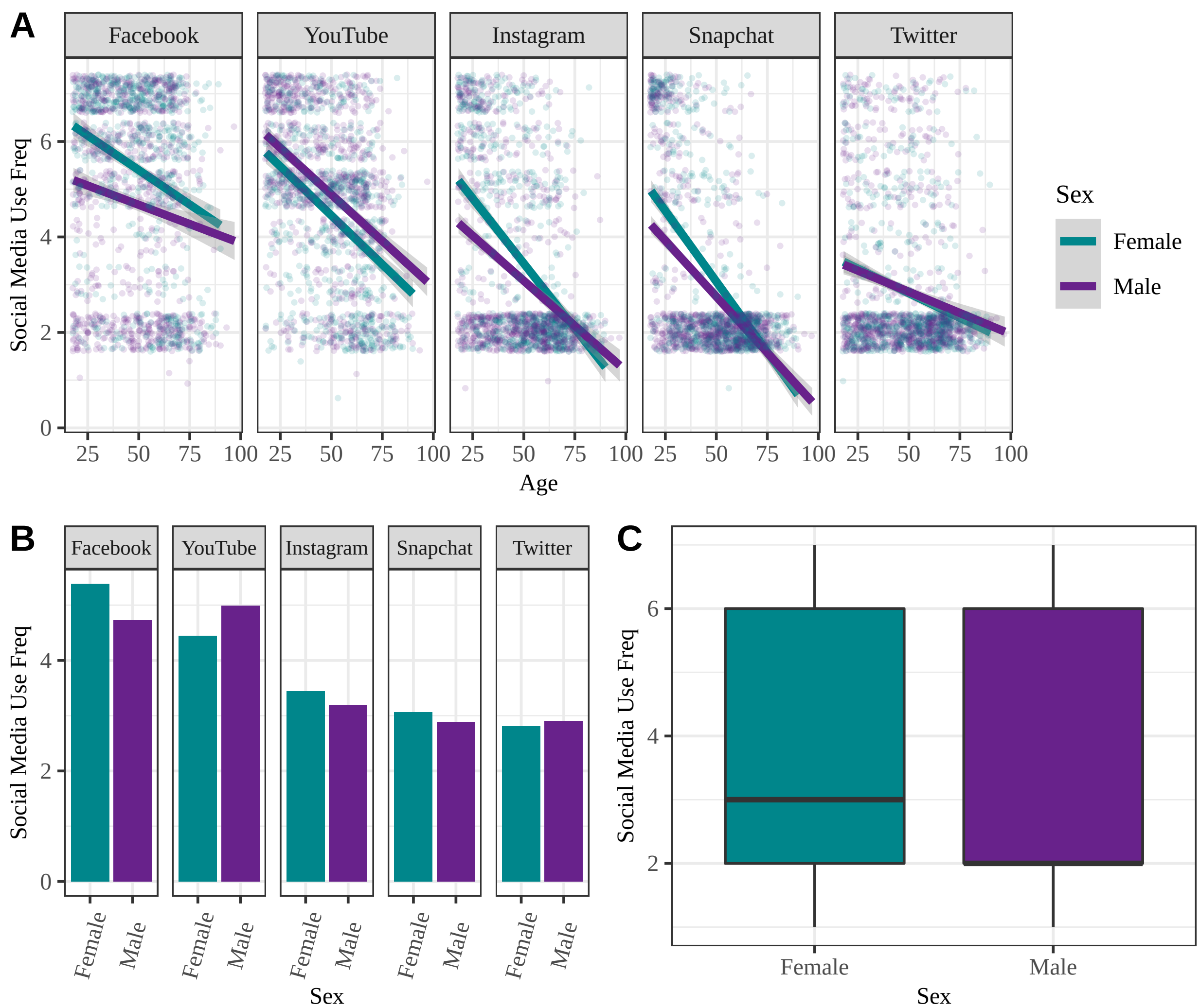

Figure 2. Frequency of social media use as a function of (a) the (non-significant) three-way interaction between age, sex, and social media site, (b) the interaction between sex and social media site, and (c) sex alone

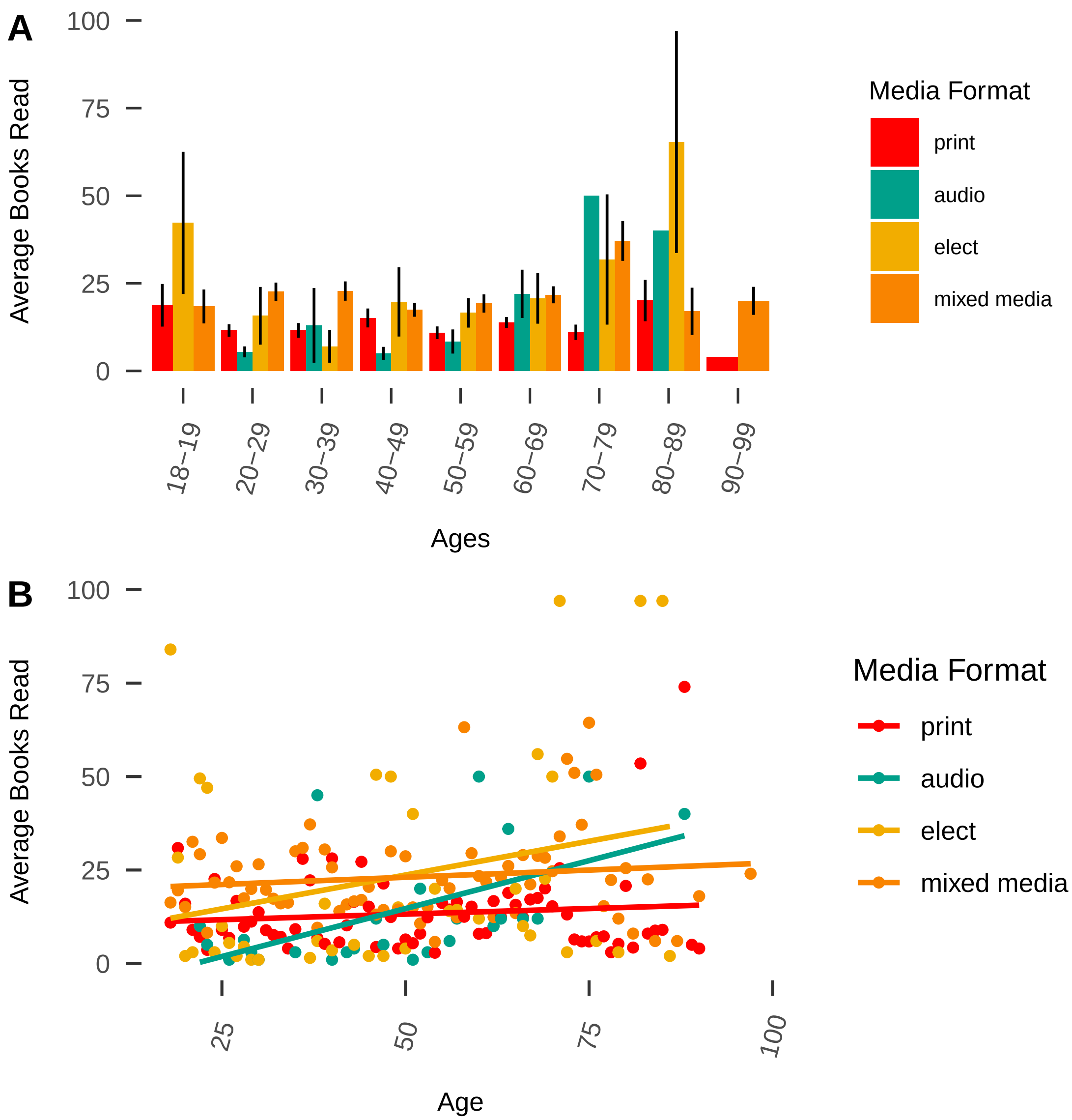

Figure 3. (a) Average books read in the past year grouped by age and media format, (b) Relationships between age and media format predicting average books read in the past year