The Perceived Time Theft of TikTok

The Influence of Self-Assessed Social Media Addiction on the Accuracy of Estimating Time Spent on Social Media: A Study among TikTok Users

RICK VAN LEEUWEN, University of Twente, The Netherlands

ABSTRACT

Social media is used on a daily basis by most people around the world, numerous studies have and are investigating the effects of this. Many of these studies rely on self report measures which have been shown to be inaccurate. This study investigates a suggested cause of self report error by evaluating the relationship between self assessed social media addiction and the ability to accurately estimate usage time. This study involved 33 student TikTok users in an experiment that entailed a browsing session and a questionnaire. The results showed an overestimation and a non significant weak correlation (p=.134) between the degree of overestimation and the degree of self assessed addiction. Further research is recommended to improve social media research by investigating the overestimation effect or using logged usage data. Furthermore, a feature is proposed that could facilitate the use of logged data by researchers.

Additional Key Words and Phrases: Social media, Addiction, Time estimation, TikTok

1 INTRODUCTION

The use of social media in modern society is nearly inevitable for an individual, with 4.7 billion social media users in 2023 [16]. Communication, education and entertainment, social media applications offer it all. The largest social media platforms, including Facebook and its subsidiaries Instagram and WhatsApp, as well as YouTube, WeChat, and TikTok, boast over one billion monthly active users each [16]. The companies that offer these platforms typically sell the attention of their users to advertisers or buyers [35]. Thus, the longer they can keep the users on their platform, the more money they will earn. Six different mechanisms are actively used by most of these platforms to prolong time spent on the platform [20]:

- Endless scrolling immerses the user without creating a natural stopping point, while also employing intermittent conditioning principles (e.g. discovering interesting or entertaining content)
- A uniquely personal social media feed, the endowment effect is leveraged to achieve an attachment and sense of ownership making it hard to give it up [15]. On top of that the exposure effect is utilised to create a preference for the platform and specific content creators which reinforces users to keep coming back [36].
- Social pressure is introduced by features such as the blue ticks that show when someone else has read a message, which creates pressure to immediately respond. The fear of missing out (FOMO) on an activity with people from a users social network stimulates the urge to be online more [23].
- Content preferences are calculated by an algorithm: data of time watched or some kind of interaction (comment or like etc) is used to decide which content piece is the next one and has the highest chance of keeping the user active.
- Social reward: More likes on a users post result in more activity in the reward area in the brain[28]. On top of that the human need for social comparison is fulfilled by the unprecedented opportunities to do so on modern social media platforms [32].
- The Zeigarnik/Ovsiankina effect: Emotional strain and a desire to finish a task when interrupted. This can also be observed within social media as the desire to finish watching a video (e.g. on YouTube or TikTok).

These technological mechanisms of social media platforms have contributed to an increasing average daily use time, which reached 2 hours and 31 minutes in 2022 [16].

In the time spent online, the user is exposed to several features of social media, one of which is the opportunity for social comparison [3]. Although there is some controversy in results between different studies there seems to be a negative link between social media use and well being, with a mediating role for the individuals mindset [1, 18, 19, 21, 26, 32]. One of the causes of the negative link seems to be upward social comparison [18, 26, 32]. Although it is a basic feature of humans, social media allows for more social comparison opportunities then ever before [3, 32]. Combined with the fact that most often the positive highlights are posted on social media it is rather easy to get the impression that everybody else has more friends, fun or happiness compared to the user itself. There have been several experiments/interventions with the aim to reduce the negative effect on well being, Reed et al.[24] let users spend less time on social media which resulted in improved well being, inconsistencies remained with other studies not finding the same results [5, 7].

The previous paragraph touches upon the large body of research regarding the effects of social media and potential interventions to improve social media as well [17, 18, 34]. However, there are several things that make research into this topic hard. First, it can be considered a moving target problem, due to the constantly changing and evolving social media platforms it is difficult to study and define it. Secondly, an intervention might not have an immediate effect but rather have long term effects or vice versa. Thirdly, social media is used in so many different situations that it is hard to study authentic social media behaviour in a controlled lab environment. Fourthly, to conduct reliable research, rigid methods are necessary.

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One problem with this is that most studies use a form of self reporting when assessing the social media use of participants, however, self reporting social media use tends to show no correlation between the logged time and the estimated time, with a trend for over estimates [4, 6, 10, 13, 14, 27, 31]. Thus the first step to study interventions that aim to reduce negative effects of social media, would be to ensure accurate assessments of the use time of social media. This research aims to explore one of the suggested causes by evaluating the relation between self assessed social media addiction among students and the ability to accurately estimate their social media use, as stated in the research question below.

- To what extent does self assessed social media addiction influence the accuracy of self reporting social media use?

The following sub-research questions support the answer to the research question:

- What is the relationship between the estimated use time and the actual use time?
- What is the relation between prediction accuracy and high or low levels of social media addiction?

The remaining chapters of this paper are: Related work, Method, Results, Discussion and Conclusion. Where related work discusses several papers on the phenomenon of overestimation among social media users and suggested causes, The Method and Results contain the research procedure, the data analysis plan and the results of said data analysis plan. The discussion evaluates the results in light of the research questions and literature whereas the conclusion mentions the significant findings, what these findings mean and a related future research suggestion.

2 RELATED WORK

Social media research largely relies on self-report measures with a small number of studies using objective assessments[11]. These self-reports of time spent on social media tend to be moderately correlated or not correlated at all with logged use[22]. Prior work found that the user overestimates their time spent on social media[4, 6, 10, 13, 14, 27, 31]. The cause of the overestimates is still unknown, however there are some suggestions. One study found that among Facebook users demographic variables are of influence, with teens and younger adults more often misreporting their time, as well as users that spent more time on the platform[9]. Another study also found a relation between amount of use and the degree of error in the estimation, as well as the well being of the user being of influence[27]. Contradicting this finding, is another study that found no influence of individual differences (personality traits), daily states (mood) and well being on the degree of overestimating use[13]. A user spending more time on a platform will create a distinction between heavy and light users, it was found that heavy users overestimate their use more than light users do[8]. One suggested cause of the inaccuracy is that the estimate of the user is not the actual use but rather the perceived use[27]. The ability to use logged time depends on the user since they have to share their logged data with the researchers. There are different methods of tracking, most individual social media applications track the use time of a user and share this data with the user in a tab in the settings. Different operating systems also track the use of the phone in general but also more specifically of individual applications. A third option is installing a third party application that tracks time spent on all applications. Having these modern tools available, researchers still depend on participants sharing their data from these tracking tools. This research will add to the pool of available literature by looking at the accuracy of an estimate during a single TikTok browsing session and an estimation of the use of the past week, by comparing the estimates with the actual logged time. Based on mentioned literature in this chapter it is be expected that a higher degree of addiction leads to a higher degree of overestimation.

3 METHOD

3.1 Participants

Student TikTok users (N = 33) were recruited at the University of Twente. Students were recruited by asking them if they used TikTok and if they had approximately fifteen minutes to participate in an experiment. Additionally, the experiment setup was briefly explained and participation in a raffle for a 15€ Pathé gift card was offered as an incentive. The choice to focus on TikTok and not other Social Media platforms was made due to TikTok having "the highest average monthly use per user" in 2022 [16]. Ethical approval was obtained from the Computer & Information Sciences Ethics Committee at the University of Twente, and oral consent was obtained from participating students.

3.2 Experiment setup

The research procedure consisted of four activities for the participants:

- Asked to participate if the student uses TikTok. Information about the experiment is shared: it will take roughly fifteen minutes, it involves privately scrolling their own TikTok feed and a questionnaire. The participants were intentionally not told any time indication for the TikTok browsing session.
- The participant was left alone in a private room for seven minutes. The participant had been asked to browse their TikTok feed until the researcher came back.
- The participant was provided a questionnaire and instructed to fill it in while the researcher waited outside the room and could be contacted if any questions were unclear. The participant was also told that all answers are completely anonymous.
- The participant was debriefed and contact details were noted in a separate file in case they won the raffle.

3.3 The questionnaire

The first question in the questionnaire was: "How long do you estimate you just spend on TikTok?". Followed up by the Social Media Addiction Scale - Student Form (SMAS-SF), a scale consisting of twenty nine questions to be answered on a Likert scale from strongly disagree to strongly agree [25]. The scale was specifically developed for students and is meant to be a self-assessment of social media addiction. This scale was chosen because the most used scale, the Bergen Social Media Addiction Scale, being less reliable when testing on students only [33]. The next question was: "How many hours do your estimate you spent on TikTok last week?". It should be noted that filling in the SMAS-SF before this question might have an influence on the answer, reversing the order could similarly influence the SMAS-SF results. Thus this order was chosen with the aim of minimising the influence of the first asked on the second asked item. After this estimate, instructions were written to access TikTok and report the logged time spent on TikTok during the previous week. The last five questions were mainly gathering the demographics of the participant, asking for gender, age, nationality and study program as well as their most used social media platform.

3.4 Data Analysis

Descriptive statistics were used to display the demographic characteristics of the sample. A score for the SMAS-SF was calculated by giving the five answers a score from 1 to 5 where 1 represented "Strongly disagree" and 5 "Strongly agree", and consequently adding up the scores for all twenty nine questions. Descriptive statistics were run to illustrate the self-assessment on the SMAS-SF. Correlations were examined to evaluate the relationship between actual and estimated TikTok use of the previous week. Two variables were created subtracting the estimated time from the actual time for the seven minute session and the estimate of the previous week. These variables were then tested for correlation with each other and with the total score of the SMAS-SF. A paired-sample t-test was conducted to test the difference between actual and the estimated TikTok use. A one sample t-test was conducted to evaluate the difference between the estimate and the timed seven minutes. The one sample t-test was repeated with six removed responses that were unlikely to be an unbiased estimate due to being exactly equal to the mentioned duration of the experiment. Additionally a cross-analysis of the data was performed to uncover any hidden or unexpected patterns.

4 RESULTS

4.1 Demographics

There were 33 participants, three responses have been removed due to invalid answers on the questionnaire. Seventy-six percent of the participants were female. The mean age of the participants was 20.9 (SD=1.7) with a range from 18 to 26 and a median of 21. In terms of nationality, the sample was mostly Dutch, with 70% of the participants. Additionally, 9% of the sample was Spanish, 3% were Brazilian, 3% were Polish, 3% were British, 3% were Colombian, and 3% were Kuwaiti. The study program of the participants was more diverse with 39% studying Technical Medicine, 19% studying Biomedical Engineering, 16% studying Creative Technology, 7% studying Communication Science, 7% studying Industrial Engineering and Management, 3% studying International Business Administration, and 3% Technical Computer Science. The reported favorite social media platform turned out to be TikTok, with 45% of participants, moreover, Instagram was chosen by 29%, Whatsapp by 19%, and Snapchat by 7%.

4.2 Estimates and Self-assessment

On average students estimated the seven minute browsing session to have been 10.1 (10 minutes and 6 seconds) minutes (N=30, SD=3.0). A visualisation of the estimates is shown in Figure 1. Removing responses that estimated 15 minutes which could have been bases on

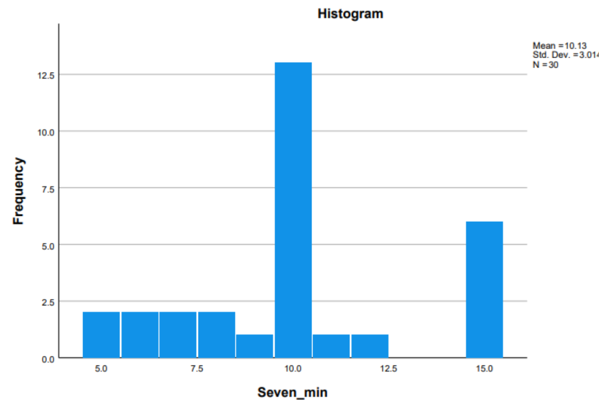

Fig. 1. Histogram of the estimates of the single browsing session

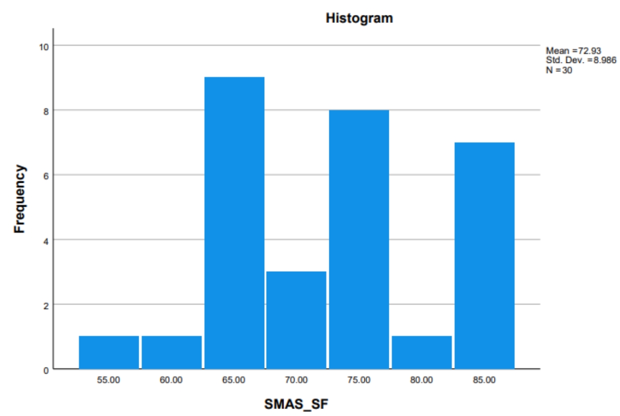

Fig. 2. Histogram of the SMAS-SF data

the given information that the experiment would take approximately 15 minutes, the average is 8.9 minutes (N=24, SD=1.9). The self assessed addiction scale (α=.73) showed an average score of 72.9 (N=30, SD=9.0) with a minimum of 55 and a maximum at 87. The data is visualised in Figure 2. The highest possible score would be 145 if every question was answered with "Strongly Agree", similarly 25 would be the lowest score if every question was answered with "Strongly Disagree". There is no definitive score when a respondent is considered addicted, instead it can be said that the higher the score, the more addicted a respondent considers themselves. The estimation of TikTok use in the previous week was on average 429 minutes (N=30, SD=319). The reported logged time by TikTok was on average 386 minutes (N=30, SD=344). The difference between the estimate and the logged time was on average 44 minutes (N=30, SD=155), which can be visually inspected in Figure 3

4.3 Correlations

Curve estimation revealed that there was no linear relationship between any of the variables. Thus the Spearman Rank-Order Correlation was used. A significant strong positive correlation was found

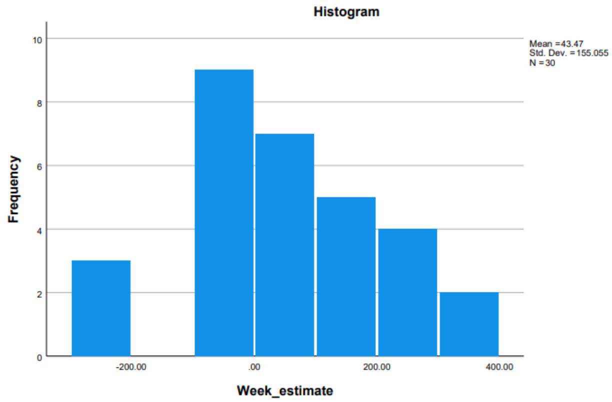

Fig. 3. Histogram of the estimate of previous week - logged data

between the estimate of the previous week and the reported logged time (r(df=28)=.89, p<.001). For the rest of this paragraph, when referred to estimates it refers to the variables created by subtracting seven minutes or the reported logged time from the estimates. There was a non-significant positive weak correlation between the seven minute estimate and the SMAS-SF results (r(df=28)=.28, p=.134). A correlation between the previous week estimate and the SMAS-SF was not found and neither significant (r(df=28)=-.01, p=.961). The correlation between both estimates was a non-significant positive weak correlation (r(df=28)=.28, p=.138).

4.4 t-tests

A one sample t-test indicated that the estimated time of the browsing session was significantly higher than seven minutes (M=10, SD=3), t(df=29)=5.694, p<.001, Cohen's d=1.0. Conducting the one sample t-test again with six removed responses, that could be viewed as biased, still yields that the estimate is significantly higher than seven minutes (M=8.9, SD 1.9), t(df=23)=4.861, p<.001, Cohen's d=.99. A paired-sample t-test showed that the estimate of the previous week (M=429, SD=319) is not significantly higher than the reported logged time spent on TikTok (M=386, SD=344) t(df=29)=1.533, p=.136, Cohen's d=.28.

4.5 Cross-analysis

For the cross-analysis, the three main variables: SMAS-SF score, seven minute estimate and weekly estimate (estimate - logged) were tested for differences between sub groups in the demographic data. A Spearman Rank-Order Correlation showed there was no correlation between age and the SMAS-SF results (r(df=28)=.004, p=.983).

4.5.1 Male/Female.

The SMAS-SF results were split into two groups as can be seen in Table 1. No significant deviations from normality allowed for the Welch t test to be used, which revealed that females score significantly higher on the SMAS-SF t(df=21.2)=2.572, p=.018. Descriptive statistics on the estimate of the previous week can be seen in Table 2, there was no significant difference, t(df=9.4)=.24, p=.815. The estimate of the seven minute session deviated significantly from a normal distribution as can be seen in Table 3, thus the Mann-Whitney U test was used and showed there was no significant difference between the groups (U=58, p=.258).

	Male	Female
N	7	23
Mean	67.7	74.5
Standard Deviation	7.7	9.4
Shapiro-Wilk p	.158	.173

Table 1. SMAS-SF data for Male and Female

	Male	Female
N	7	23
Mean	30.4	47.4
Standard Deviation	167	155
Shapiro-Wilk p	.803	.605

Table 2. Week estimate for Male and Female

	Male	Female
N	7	23
Mean	11.3	9.8
Standard Deviation	3.9	2.7
Shapiro-Wilk p	.218	.005

Table 3. Seven minute session estimate for Male and Female

4.5.2 Dutch/Other.

Due to the majority of the sample being Dutch and other nationalities not having many respondents, all the different nationalities were put together in the "Other" group. Table 4 shows the descriptive statistics for the SMAS-SF between Dutch and Other nationalities, the Welch t test showed there to be no significant difference t(df=12.4)=.971, p=.350. Table 5 and Table 6 show the descriptive statistics for the week estimate and the single session estimate respectively. The Welch t test for the week estimate showed no significant difference, t(df=16.2)=-0.81, p=.937, and the Man Whitney U test no significant difference either (U=92.5, p=729).

	Dutch	Other
N	20	10
Mean	74.3	70.3
Standard Deviation	7.2	11.8
Shapiro-Wilk p	.18	.12

Table 4. SMAS-SF data for Dutch and Other nationalities

	Dutch	Other
N	20	10
Mean	79.4	-28.3
Standard Deviation	156	132
Shapiro-Wilk p	.241	.16

Table 5. Week estimate data for Dutch and Other nationalities

	Dutch	Other
N	20	10
Mean	10.1	10.2
Standard Deviation	2.9	3.3
Shapiro-Wilk p	.006	.558

Table 6. Single session data for Dutch and Other nationalities

4.5.3 *TikTok/Other.*

The last cross-analysis was performed on the favorite social media of the participants, comparing the group that reported TikTok with the group that reported any other social media platform. Some answers were unclear by stating "TikTok or Whatsapp", these responses were not included in this analysis. The descriptive data for SMAS-SF, the week estimate and the seven minute estimate can be seen in Table 7, Table 8 and Table 9. The Welch t test for the SMAS-SF score t(df=25.8)=1.406, p=.172 and the weekly estimate t(df=26.0)=.746, p=.463 yielded no significant differences. Neither did the Mann Whitney U test for the seven minute estimate (U=78.5, p=.359) yield a significant difference.

	TikTok	Other
N	13	14
Mean	75.0	70.6
Standard Deviation	8.7	9.4
Shapiro-Wilk p	.062	.953

Table 7. SMAS-SF data for TikTok and Other group

	TikTok	Other
N	13	14
Mean	4.8	78.9
Standard Deviation	179	132
Shapiro-Wilk p	.501	.078

Table 8. Week estimate data for TikTok and Other group

	TikTok	Other
N	13	14
Mean	10.8	9.9
Standard Deviation	2.8	3.2
Shapiro-Wilk p	.062	.046

Table 9. Single session data for TikTok and Other group

5 DISCUSSION

5.1 Research questions

The main research question to be evaluated is: "To what extent does self assessed social media addiction influence the accuracy of self reporting social media use?". To answer this question the following two sub research questions are answered first:

5.1.1 *What is the relationship between the estimated use time and the actual use time?*

Two different variables were used to measure the accuracy of the estimated time, one for a single browsing session and one for the TikTok use of the previous week. The first variable showed a significant over estimation of three minutes (p<.001). When removing some potentially biased responses from the data, there was still a significant overestimation of almost two minutes (p<.001). The removed responses could be explained by the fact that participants were informed that the experiment would take approximately fifteen minutes and therefore assumed they had been browsing fifteen minutes when asked to estimate for how long they had been browsing. Another thing to be noted is that many estimates were ten minutes as can be seen in Figure 1, this could be due to the human construct of time which is often rounded off in steps of five minutes (e.g. 5 past 6 or 10 to 6), but that is unknown and something worth investigating more. To conclude, when letting users privately browse TikTok for seven minutes, it was perceived as being 9 or 10 minutes which is in line with earlier findings of overestimation [4, 6, 10, 13, 14, 27, 31]. The second variable showed that estimated time and actual logged time spent on TikTok are strongly positively correlated (p<.001) which contradicts earlier findings that found no correlation or only a moderate correlation [22]. Additionally, the estimation was found to on average be 44 minutes higher (SD=155), however, it was a non-significant (p=.136) difference while an overestimation was to be expected based on the found literature [4, 6, 10, 13, 14, 27, 31]. Comparing the TikTok use of the participants with the global overview of 2022, shows a monthly TikTok use of 25 hours and 36 minutes among participants compared to an global average of 23 hours and 28 minutes, which is not an abnormal difference [16]. Thus for the single browsing session there is a relation between the estimated time and the actual time, while for estimates about the previous week there is no clear relation except a slightly higher mean which could have been found by chance.

5.1.2 *What is the relationship between prediction accuracy and high or low levels of self assessed social media addiction?*

To evaluate if there is a relationship between prediction accuracy and differing levels of self assessed social media addiction, a correlation analysis was conducted. The two variables that were created by subtracting the actual time from the estimate were checked for any correlation with the SMAS-SF results using a Spearman Rank-Order Correlation. The overestimation in the seven minute browsing session, was found to be a non-significant weak positive correlation (p=.134). The estimate of TikTok use in the previous week, showed to be a non-significant not correlated (p=.961) one. Thus it cannot be concluded that the ability of users to estimate their own use time is related to differing levels of self assessed social media addiction, which is not in line with the findings in literature that suggest that heavy users (thus also addicted users) overestimate their social media use more than light users [8].

5.1.3 *To what extent does self assessed social media addiction influence the accuracy of self reporting social media use?*

The hypothesised relation between prediction accuracy and varying levels of self assessed social media addiction could not be proven. Thus, it can be concluded that this study does not find any influence of self assessed social media addiction on the ability to estimate use time. There is a hint that an overestimation, which was found in this study, is weakly positively correlated but this could not be significantly shown.

5.2 Limitations

There are several limitations to this study that could have influenced the results in a way that reduces generalisability. The first identified limitation is that a majority of the sample is female and/or Dutch. Although the participants were asked to participate at random, these majorities could create biased results. A second limitation is the relatively small sample size, it could be that results with more significance would have been found if the sample size was larger. The difficulty with this is that it takes a lot of time and enough willing participants have to be found, many students did not meet the inclusion criteria (Be a TikTok user) or preferred to spend their time on their own study load. This also introduces the possibility that students that were willing to participate are in some way different (curiosity or openness) than the students that did not wish to participate. A third limitation is the ever changing nature of social media platforms, including TikTok. It could be that findings in the past are not applicable anymore due to changes to the platform or that the platform changes in such a way that a replication of this study yields different results in the future. A fourth limitation is the fact that participants want to know (rightfully) an approximate duration of the experiment to judge if they want to participate, which introduces an anchor in the used research procedure, thus the discovered over estimation could be due to the anchoring effect of the mentioned fifteen minutes duration [12, 29]. Lastly, the questionnaires were filled in while privately in a room, thus students could have reported a different logged time of TikTok use than they actually had due to a multiplicity of reasons which would influence the found results of this study as well.

5.3 Future work

Given the results and limitations of this study, several relevant research opportunities can be discovered. To start it would be interesting to test what the results of this study setup would be with a larger sample. Furthermore, the research should be expanded to other social media platforms, testing if the results would be different or similar. It could be interesting to compare the results of this study with another similar study with only a minor difference in the single browsing session, changing the time to be browsed to shorter or longer alternative, and evaluate the implications of this change. Lastly, one of the features of TikTok is that it creates a personal "For you page" (FYP) which gives a user content according to the likes of the user, thus improving with more use. A study that evaluates differences in time perception between a user on their own FYP and a user with a brand new account would be interesting, as it could be expected that time perception is worse when browsing an optimized FYP TikTok feed. Lastly, it is recommended to look into the finding that females score higher on the SMAS-SF which could be related to shown gender differences in social comparison [2, 30].

5.4 Proposed feature

The effect of overestimation remains when users are asked to report their own use time of social media applications. In this paragraph a feature is proposed that could facilitate social media research and the use of logged data instead of self reported data. Using logged use data would improve social media research in the way that it ensures it is based on reality instead of inaccurate self perceptions of time. The proposed feature would require recognised researchers to request a "researcher code" on a specific social media platform. This code could be shared with willing participants or via online mediums such as email or social media. The platform should implement a tab in their settings where users could enter a the "researcher code" to enroll them into the study of this researcher. Before confirming the enrollment an info sheet about the study could be shown to ensure an informed consent by the user. Once an user is enrolled, the researcher will have access to the logged time of use by that user as well as a way to contact (Direct messaging or email) the user to share questionnaires. The data can be gathered for different periods of time, allowing longitudinal as well as cross-sectional studies. Such a feature would significantly lower the barrier for users to enter in studies as participants and for researchers to gather logged use data from a large potential sample population. Nevertheless, such a feature is not available yet, thus for the time being researchers have a responsibility to treat their social media research with caution as long as self reporting is used.

6 CONCLUSION

The research procedure contained a single browsing session on TikTok that was timed to be seven minutes, which was unknown to the participants, after which they had to estimate the length of that session. A one sample t-test on the estimates revealed that users tend to overestimate the time of the single browsing session. This adds to the body of literature on the overestimation effect, especially since a similar research on TikTok and a single browsing session was not performed before. It also warrants further research into the unknown causes of the overestimation effect, partially because this study could not find significant evidence for a suggested cause, heavy use (including addiction). Additionally, results showed that female TikTok users assessed themselves as more addicted compared to male TikTok users. Which is an interesting finding in the light of already existing gender differences in relation to social media. Further research is recommended to investigate and explore the causes and effects of this phenomenon. As a new generation is growing up with everyday use of TikTok and social media, thus it is hugely important to understand or mitigate negative effects of social media. Therefore, future research into this topic is necessary, with a specific encouragement to use logged data instead of self reported data.

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