Our sweetest hours fly fastest… on smartphone.

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Abstract

The steady increase in time spent on smartphone applications and particularly on social networks, raises questions about the environmental and societal sustainability of such a phenomenon. Utility and enjoyment have a key role in such practices, but other factors such as passing time may also contribute. From May to November 2023, 5,028 people took part in a web survey aiming at producing durations prospectively using mobile applications like Facebook, Instagram, TikTok, Reading. The protocol introduces variables known to have an effect on time perception. On average, the produced durations were underestimated. This result is in line with the notion that tracking information and tracking time compete for the brain's limited attentional resources and, hence, that attention plays a critical role in time estimation. Significant differences emerged between the applications tested. TikTok and Reading tasks appear the most underestimate but with opposite dynamics as the level of *satisfaction* and *familiarity* are lower for the first compared to the former. Among the variables studied to explain the difficulties in evaluating time spent, the importance of *familiarity* with the activity is undoubtedly something worth exploring in the context of the race between new algorithms and cognitive adaptability.

Keywords: Smartphone; Usage; Behavior monitoring; Regulation; Self-report; Time perception; Attention.

Introduction:

Thanks to a pervasive internet connection, smartphone usage has exploded in recent years (Statista, 2021). Young people have doubled their screen time in ten years (Ofcom, 2021) with numerous consequences on intra- and inter-individual psycho-social variables (see Dickson et al., 2019, for a meta-analysis). From a medical point of view, studies highlight the deleterious effects of excessive screen use, in particular on sleep quality (Wang &, Scherr, 2022), obesity (Robinson & al. 2016), attention and behavior in general (S. Tang & al., 2021).

Accurate self-measurement and metacognition are presuppositions for sound decision making, especially when it comes to investing time (Koriat, 2015; Ackerman, 2014). The ability to estimate the time spent on smartphone applications therefore needs to be studied in detail, under real conditions and with a sufficient sample (Josset et al, 2022).

Two distinct cognitive functions alter the ability to evaluate durations (prospectively and retrospectively): attention to time and cognitive or executive load (Block & Gruber, 2014; Nicolaï et al., 2024). In the first case, selective attention is an essential capacity that enables the brain to allocate its cognitive resources to the analysis of information relevant to a given action or behavior. When using an app, "attentional capture" means that the information provided by the app will conflict with the individual's ability to evaluate time spent on the app. This first factor could contribute to the impression of wasted time; however, this "wasted time" is fictitious, since it substitutes and presents itself as a compromise to boredom. "Mental load" is a second factor that has a parametric influence on the amount of time experienced or remembered: in a given time lapse, the greater the mental load, the more the duration experienced will be underestimated. This mental load can be operationalized by several parameters. Actualization or "update" seems to be the main factor affecting the loss of time experienced in this type of paradigm (Ogden et al., 2011). These two cognitive variables can be tested concomitantly (Polti, Martin, van Wassenhove, 2018). A third aspect to consider is metacognition, and notably the new exploratory field of temporal metacognition. Individuals not only have the ability to estimate duration (via temporal production, for example), they are also able to self-assess their errors and estimate the extent to which their initial estimates are accurate or inaccurate (Akdoğan & Balcı, 2017; Kononowicz, Roger, van Wassenhove, 2020).

Attentional capture and mental load can not only affect the individual's immediate experience, they are also likely to alter or modulate the ability to self-assess the time spent on an activity, either leading to temporal disorientation (through lack of encoding of durations and temporal cues, memory hypothesis), or through volitional disengagement (through attentional capture, attentional hypothesis).

Many of these studies have been realized in a laboratory-controlled environment – although during the COVID-19 pandemic some on time experience (Cravo et al., 2022) or subjective temporalities (Chaumon et al., 2022) have been conducted –, with standardized tools, but we know that smartphone applications use algorithms aimed at extreme personalization of the content offered to increase stickiness. Complementary, our study aims to test user behavior in "real life", meaning using their own smartphone and their own applications, tailored to their profile.

State of art:

With substantial amounts of time devoted to video games, the Internet and social networks, several studies have been carried out on these uses, but more often to study their consequences than to understand why, beyond the utility and pleasure they provide. Tobin & Grondin (2009) show that, adolescents tended to estimate the target duration of 8 min for playing games to be shorter than for reading, in line with the hypothesis that they underestimate the time spent playing. This result might be explained by the fact that playing Tetris requires greater mental effort than reading, and consequently less attention is paid to temporal judgment. Bisson & Grondin (2013) studied, with young adults, the accuracy and variability of prospective and retrospective temporal estimates with surfing the web and playing a video game task. They found out that the time dedicated to video games is considerably underestimated compared to the Internet browsing task, which is itself underestimated, and explain this result with an interference effect, impacting attention. Additionally, a test measuring subjective cognitive load (NASA TLX) established that participants perceived the Internet browsing task as less demanding than the video game task. Gonidis & Sharma (2017) in a perspective focused on digital addiction issues found that users underestimated the time they were spending on Facebook, findings which may be even more so applicable to TikTok users considering the fast-paced nature of the platform.

At the end of this review, we ask ourselves several questions : can we compare estimations of the duration of all these different digital activities done in the same context/moment ? Secondly, if there are some differences between those estimates, which variables best explain them : age, familiarity, enjoyment… ? And finally, questions arise about meta-cognition on these estimates : accuracy awareness, depending of the activity ?

Method:

The web survey tested prospective duration tasks in which participants were asked to use an app for a certain amount of time with digital devices (smartphone, tablet, laptop). The six consecutive tasks were: reading news, Facebook, TikTok, Instagram, playing a game, and an activity of the participant's choice (coded: free). These activities were proposed in a pseudo-random order to each participant.

For each activity, a duration target was proposed ranging from 30 to 90 seconds (uniform distribution). To produce the requested duration, the participant had to use an app or performed an activity for the requested amount of time. After performing an activity, participants rated their *confidence* level in the time production task, their *satisfaction* and their *familiarity* with the application. They could then move on to the next task.

After completing all tasks, participants were asked additional questions about their general experience of the survey: they rated their feelings of *joy*, *sadness*, *impatience*, *boredom*, and provided a global rating of their passage-of-time judgements implemented as Likert scales offering a categorical choice among 'very slow', 'slow', 'normal', 'fast' and 'very fast'.

None of the 6 tasks were compulsory, but at least one had to be completed to validate the test.

Respondents were recruited from "The LAB", a panel of around 15,000 subscribers managed by the Telco company Orange to carry out marketing and research surveys on innovative products and usages. The "Time Survey" was posted on the LAB 's homepage as one of the available web surveys for a 6-month period. The collected data complied with the Orange internal ethical review board and the resulting data were anonymized in compliance with personal data protection rules.

Results [1] :

From May to November 2023, 5,028 people took part in the survey, completing a total of 18,703 tests (on average, 3.72 tasks per person). 3,893 (73%) surveys were completed by men, 1,121 (26%) by women. 3 people answered "other" and 11 did not wish to answer. The average age was 47 y/o, ranging from 17 to 89. The age pyramids for both men and women followed a bell-shaped normal distribution around the means: 47 for men, 46 for women (skewness = 0.09).

Figures 1 and 2 plot the produced duration (in sec) as a function of the target duration (in sec). The first figure represents the cumulative duration of all tasks per participant. All duration targets ranged from 30 to 428 sec while produced durations varied between 10 (protocol driven minimum for a test) to 873 sec (x2). One dot is an individual's prospective duration in one task. While the locally weighted smoothing line (lowess) roughly follows the symmetry line, the dispersion of the points increases regularly. Figure 2 plots the same variables but broken down for each task or application tested (note: for the sake of readability, the dots are not shown on this graph).

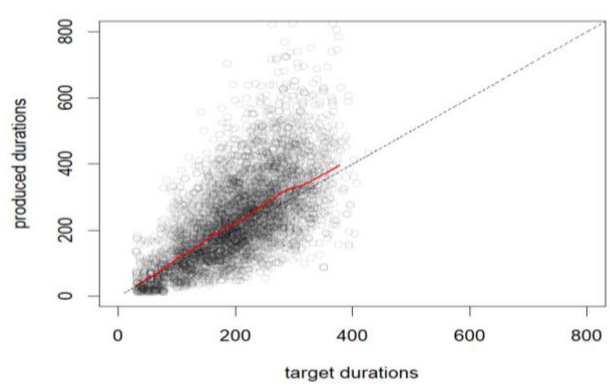

Figure 1. Cumulative target and producted durations

[1] Data analysis done with RStudio 2023.09.1.

Figure 2 below shows that producing a duration through a Reading activity yields an overproduced duration. TikTok follows this trend in a more irregular way. It also seems that, for a major part of the tasks, at around 60 sec the duration produced gradually approaches the target and drops below afterwards.

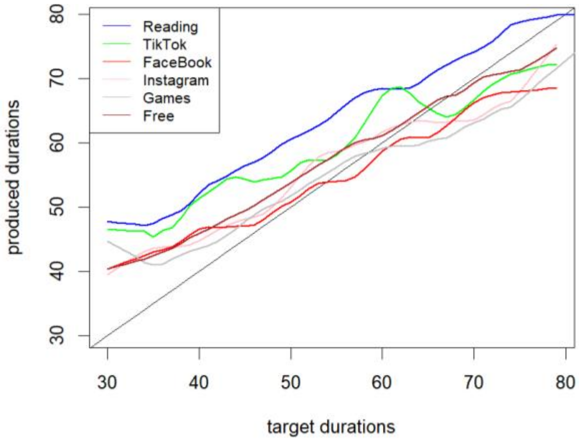

Figure 2. Target and producted durations by *app*.

Application	Satisfaction		Familliarity		R_duration		Confidence		Count
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Facebook	3.43	0.71	3.43	1.02	1.14	0.67	55.31	24.72	3444
Free choice	3.62	0.72	3.72	1.00	1.19	0.66	55.77	24.66	4228
Games	3.55	0.75	3.39	1.01	1.16	0.70	54.84	25.21	3251
Instagram	3.56	0.71	3.42	1.01	1.19	0.73	56.06	25.62	2804
Read	3.51	0.67	3.48	0.93	1.29	0.66	54.83	21.66	3621
TikTok	3.43	0.78	3.19	1.08	1.26	0.76	55.12	24.97	1355

Figure 3. Descriptives statistics by *app*.

Figure 3 gives an overview of the results (mean and standard deviation) of the *satisfaction*, *familiarity*, and *confidence* ratings, as well as the ratio between produced and target duration (‘R_duration”: relative duration production) for each application. The mean ratio is greater than 1 for all tested applications, but with greater values for Reading and TikTok. The standard deviation is notably larger for TikTok. *Satisfaction* is evaluated after each the activity performed, with the "free" activity at the top of this category. The applications with the highest scores related to the item *familiarity* is “free” – which seems logical –, followed by reading and Facebook, TikTok coming last. To be mentioned: the source of satisfaction for *free* may be distinct from the source of satisfaction for the other activity. In the first case, it could be due to the satisfaction of having had the choice, while for the others the activity itself may be the source of satisfaction. We can assume the fact that TikTok is least familiar to the panel and directly linked to the average age of the panel. The value for the item measuring the confidence in the time duration estimation is around 55 since a lot of respondents did score this item at 50.

Figures 4 and 4b give an overview of the relationships between former variables, illustrating how applications differ. The two main factors computed by a principal factor analysis explain respectively 49% and 32% of the variability. The main contribution of the first dimension are *satisfaction* and *familiarity* whereas the *confidence* contributes mainly to the second dimension. A Clustering (Ward’s method not detailed here) confirms group made up of Instagram, Facebook, and Games, to which reading is attached first, then TikTok and lastly Free.

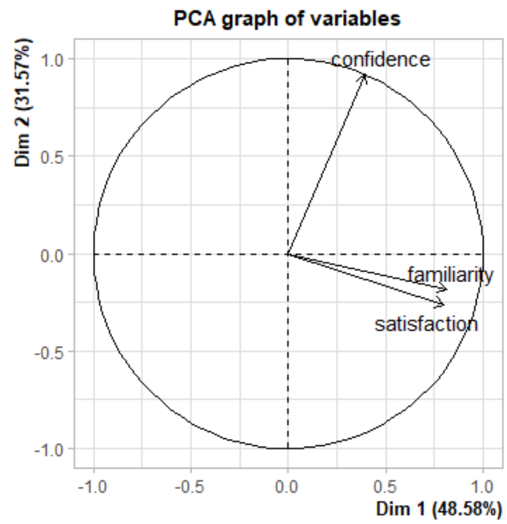

Figure 4. Principal component analysis.

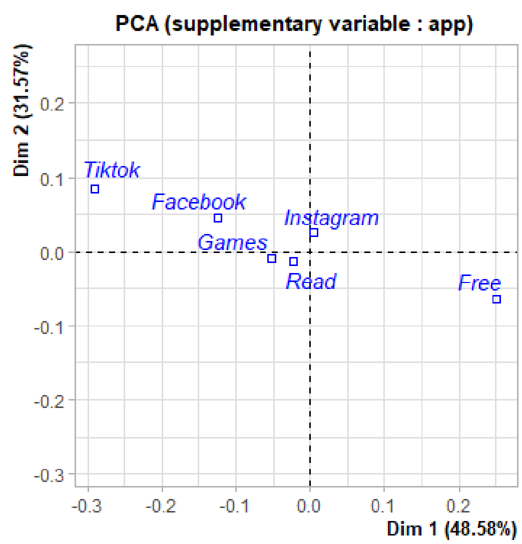

Figure 4b. Representation on the factorial planes of the *app*.

Explaining the ratio produced duration / target duration

Time estimates vary from one application to another. We have already shown that the differences may be due to differences in *familiarity* and *satisfaction* with the different tasks. Other variables may also influence duration estimates. We propose a multiple linear regression for accounting for confounding variables. As we already stated, the produced duration is generally longer than the target one, with a mean of the relative duration production (r_duration) of 1.2, varying from a minimum of 0.13 to a maximum of 6.26. The distribution shows more values to the right (median below the mean), which is confirmed with a skewness test value equal to 1.77. We then log-transformed the explained variable to follow a normal distribution.

Figure 5 shows the distribution (box plots) of transformed duration ratio (r_duration) for the main variables introduced in the model. Certain distributions stand out in particular like *satisfaction*. Another one is related to the order showing that tasks performed first are shorter than the following ones, confirmed by a pairwise t-test (Bonferroni) that shows that this difference is significant ($p<0.001$). We perform the same test for *app* and get a significative difference for *Read* and *TikTok* compared to other activities ($p<0.02$) confirming the previous descriptive analysis.

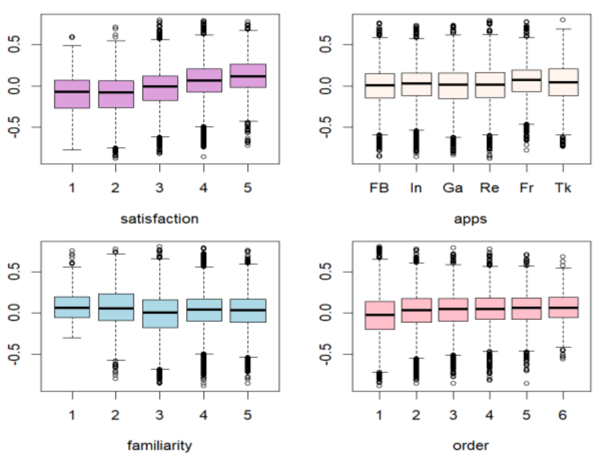

Figure 5. Box plots of transformed duration ratio (satisfaction, app, familiarity, order).

A linear regression of the transformed duration ratio with these former variables, adding *age*, *profession* and *gender* (reduced to only Male and Female as other answers are too anecdotal) is computed. We tested an interaction effect between the applications evaluated and *satisfaction* or *familiarity*, insofar as the levels may differ from one application to another, but without significant effects. A multicollinearity test was conducted (VIF <1.8) showing a low correlation between variables; normality of residuals was verified. We then performed an Anova type 2 (not reported) to test on the model to get global significance and relative weight of all variables. The main effect comes from the variable *satisfaction*, followed by the *familiarity* with the app. With less weight but still significant variables such as *age*, *profession*, *order of the test* accounts too. The regression model (figure 6) confirms the differences between applications after controlling for other variables. Compared with Facebook, reading and "tiktoking" increase the relative duration production.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
Intercept	-0.348118	0.016592	-20.98	< 2e-16 ***
Application (Ref.: Facebook)				
Free	-0.008726	0.005578	-1.56	0.118
Games	-0.014090	0.005729	-2.46	0.014 *
Instagram	-0.002445	0.005965	-0.41	0.682
Read	0.034754	0.005782	6.01	1.9e-09 ***
Tiktok	0.030872	0.007529	4.10	4.1e-05 ***
Age	0.002284	0.000176	12.96	< 2e-16 ***
Order (Ref.:Other)				
First	-0.060152	0.004184	-14.38	< 2e-16 ***
Gender (Ref.: Man)				
Female	0.009035	0.003889	2.32	0.020 *
Profession (Ref.:Other)				
Retired	0.044909	0.007239	6.20	5.6e-10 ***
Familiarity	-0.032590	0.001868	-17.44	< 2e-16 ***
Satisfaction	0.094557	0.002608	36.26	< 2e-16 ***

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.234 on 18641 degrees of freedom Multiple R-squared: 0.0948, Adjusted R-squared: 0.0942 F-statistic: 177 on 11 and 18641 DF, p-value: <2e-16.

Figure 6. Results of the multiple regression model of the duration ratio.

Cumulative duration production, passage of time judgment and temporal illusions

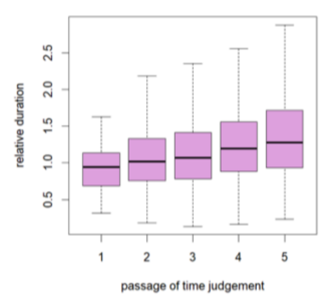

Figure 7. Cumulative duration ratio broken down by passage of time judgment.

Figure 7 shows the distribution of the cumulative duration ratio with the passage of time judgment (1: very slowly; 2: slowly; 3: normally; 4: fast; 5: very fast). Here the faster the time felt to pass, the larger the relative duration. This indicates that the overestimation of duration was associated with a faster passage of time.

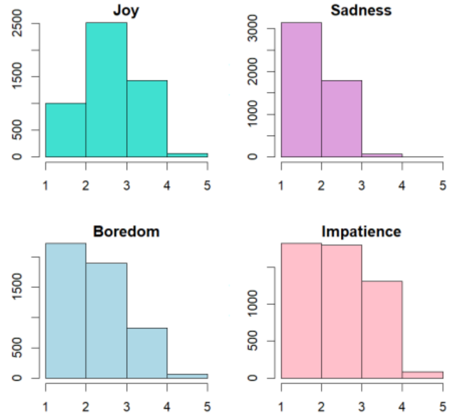

Figure 8. Distribution of *joy*, *boredom*, *impatience* and *sadness.*

Figure 8 shows the distribution of *joy*, *boredom*, *impatience* and *sadness*. Participants rated their emotion on a scale of 1 ("not at all") to 5 ("very"). The option 5 was rarely chosen; less variability emerged for *sadness* and *impatience*. We first investigated the association between these variables and the passage of time judgment, mobilizing the Kendall's Tau, suitable for data with ranked or ordinal categories. The value varies between +1 and -1. Values were 0.22 for *joy*, -0.27 for *boredom*, -0.16 for *impatience* and -0.08 for *sadness* (all with $p < 0.001$). These suggested that the speed of time was positively related to *joy* (the more joyful, the faster time felt to pass) but negatively to *boredom*, *impatience* and *sadness*.

	LR Chisq	df	p(>Chisq)
Joy	140.64	16	< 2e-16 ***
Sadness	71.93	16	4.56e-09 ***
Impatience	187.60	16	< 2e-16 ***
Boredom	253.98	16	< 2e-16 ***

Figure 9. Analysis of the multilogit regression model for passage of time judgment.

Figure 9 shows variables that are most discriminating from a multivariable regression (multilogit) model for the passage of time judgment. In our study, it appears that *boredom* and *impatience* had the greatest effects followed by *joy* and *sadness*. The coefficients not reported here are in line with the previous bivariate analysis. Contextually, the effect of *boredom* could be explained as the pool of participants received no retribution for their participation to this web survey and may have been motivated by *boredom* in the first place.

Figure 10 shows results of the relatives' effects of *joy* and *sadness impatience*, *boredom*, *gender* and *age* as regressors for cumulative duration ratio. The main effects come from *boredom*, *joy*, and *age*.

	Sum of Squares	df	F	p
Joy	23.47	4	20.0821	< 2e-16 ***
Sadness	3.29	4	2.8148	0.02391*
Impatience	3.84	4	3.2834	0.01071*
Boredom	41.68	4	35.6651	< 2e-16 ***
Gender	0.01	1	0.0488	0.82513
Age	17.06	1	58.3972	2.55e-14 ***
Residuals	1459.40	4995		

Figure 10. Analysis of the multiple regression model for cumulative duration ratio.

Summary of results:

Plotting participants' produced duration as function of target duration shows that the longer the task, the more dispersion of the plot in agreement with scalar property of timing. We also observed that produced durations are generally above the target value but getting lower after 60 seconds, in agreement with the typical central tendency effect. A sequential effect was also found in that the first tasks were underestimated whatever the activity. Comparing tasks durations, we noticed that *Reading* and *TikTok* have the highest duration/target ratio meaning a greater overproduction of duration. An overproduction of duration is indicative that participants' internal clock ran a bit slower while being engaged in the tasks. The second dimension extracted from the principal component analysis shows that the confidence level in the timing task is the opposite of the ratio between produced and target duration ('R_duration"), so that the larger the temporal errors, the least confident participants were in their temporal productions. The comparison between tasks duration further shows that participants were more familiar with *Reading* and *Facebook*, *TikTok* being the least. The application left to the free choice (*Free*) of testers was the one with the highest level of satisfaction. Concerning, *joy*, *boredom impatience sadness* and their effect on cumulative duration/target ratio and on passage of time judgment, it appears that the first is negatively associated contrary to the others. *Boredom* appears the most discriminant variables for both modeling. *Joy* also has an impact but in a least extend for passage of time judgment.

Discussion:

Not surprisingly, the duration of the task has an impact on time estimation. The web survey conducted is consistent with most studies gathered from prospective studies that have established that humans are on average accurate in their time estimates and that the variability in time estimates is overall proportional to the mean estimates (scalar property, e.g., Grondin et al., 1999; Wearden & Lejeune, 2008).

Like other judgements of quantities (e.g., length, number, colour, etc.), duration estimates present the characteristic tendency to gravitate towards their mean value (central tendency effect) as observed here around 60 seconds for produced durations. In the temporal domain, relatively short or relatively long-time intervals will be over- or under-estimated, while duration estimates of the same time intervals will be shorter or longer depending on whether they are presented in the context of short or long intervals (context-dependency) (Jazayeri & Shadlen, 2010).

Following each duration production, we asked the participants to rate their confidence level in the time production task which constitutes a metacognitive judgement and provide an assessment of temporal error monitoring. Our results tend to be in line with studies on metacognition showing that individuals are able to estimate the extent to which their initial estimates are accurate or inaccurate. Here the confidence level in the timing task is the opposite of the ratio between produced and target duration (‘R_duration”). More metrics and investigation should be computed, but this first descriptive analysis opens the discussion about the role metacognition can play for controlling and monitoring time spent on applications. For example, it could be worth to explain the mechanisms attention plays in time evaluation following the idea that the more aware people are of the role of attention in time perception, the lower the time distortions they exhibited. Metacognitive sensitivity to time plays an important role in the adjustment strategies involved in time judgment, even though these do not affect the fundamental properties of time (Lamotte et al. 2017).

The item *familiarity* and in a less extent the order of the task are related to the attention factor. Authors have reported that a high level of *familiarity* with an information processing task is likely to decrease the level of cognitive resource demands following learning of all or some of the task components (Schneider & Shiffrin, 1977). A high level of *familiarity* with a task will mobilize a smaller amount of attention to the task than a person for whom the task is new. Familiarity improves production time estimation and accuracy as our results tend to settle. Appreciation in a task translates into being cognitively engaging (away from mind-wandering), yielding to a slowing down of internal time and an overestimation of time spent in the task (attention driven away from time, and into the cognitive task of reading, tiktoking, etc). Our results show a great impact of the level of *satisfaction* evaluated for each task.

Related to the feelings about the passage of time, the time estimation and emotions experienced during the survey, we computed two investigations with similar trends: as expected the respondents tend to more underestimate time or to rate that time is passing faster when they are experiencing *joy* and at the opposite less underestimate time or to rate that time is passing slowly when they are experiencing *boredom* and *impatience.* The reason of these temporal illusions is that while having "fun”, attention is focused on the “fun” aspect and not on time and when a person waits for something to occur the main concern is time and as a result most attentional resources are focused on time (Block et al., 2018).

As for the *age*, the increase in time spent could also be explained by attentional focus and cognitive engagement.

Underestimations of duration have been related to the level of difficulty in concurrent non-temporal tasks and to the proportion of attention allocated to non-temporal features of a stimulus. Accordingly, we might infer that Instagram, Facebook, and Games are equivalent in term cognitive load. The greater underestimation of time spent in reading and on TikTok compared to the others application might refer to a greater cognitive load. TikTok, is for our panel, the least familiar activity tested, and is also known to have a large component of surprise (refreshing content under the control of the participant) and strongly engages the reward system known to contribute to timing. (Wang K, Scherr S. 2022; Montag et al. 2021).

Conclusion:

Smartphone manufacturers are promoting time monitoring as a remedy to screen overuse, while the issue of *dark patterns* designs used by certain applications to increase usage is raised. Beyond the sound corpus of laboratory literature, we wanted to observe in everyday life the biases that make it difficult to estimate durations of activities performed on smartphones. The survey we conducted on more than 5000 people confirmed many factors identified in cognitive research: bias in estimating time, importance of mental workload, and the influence of emotions. The importance of *familiarity* with the activity raises questions about the possibilities of learning and adapting to the algorithmic processes implemented by applications to increase their stickiness. “Older” applications like Facebook seemed more easily handled by our participants than a newer application like TikTok. This is in line with the studies around metacognition. This point should be studied in greater detail, using appropriate protocols and no doubt paying greater attention to the age of the participants. Maybe we'll find there some mental adaptation factors that could help face the challenge posed by screens to the attention span of future generations.

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