Time distortion in student YouTube use: The effects of use motivation, personality, and pattern of use on study efficiency

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This paper examines study efficiency and time distortion experienced by student users of YouTube. Using multi-group structural equation modelling on data from 792 Malaysian university students, the study identified links between YouTube use motivation, conscientiousness (a personality trait), time distortion, and perceived study efficiency. It also shows how these characteristics and the links between them varied when students were grouped by pattern of use, defined (using two-step cluster analysis) as occasional, regular, or problematic. Time distortion had a negative effect on perceived study efficiency, but conscientiousness counteracted this effect - particularly for occasional users, the only group with positive perceived study efficiency in this study. Motivation to use YouTube for learning was not associated with time distortion, whilst using YouTube for escape and entertainment increased motivation. Occasional users were less motivated than others to use YouTube for these purposes and therefore less likely to experience the entertainment use flow on effects of time distortion to perceived study efficiency.

Implications for practice or policy:

- Motivating students to use YouTube for learning is unlikely to reduce study efficiency.
- Use of diagnostic tools to understand a student's pattern of social media use, as well as motivation for use, personality and sense of time distortion, could help advisers identify reasons for low study efficiency.
- Digital literacy education focused on increasing self-discipline and goal-orientation could help students reduce poorly controlled use of social media for entertainment and escape, and hence improve study efficiency.

Keywords: time distortion, student usage of YouTube, use motivation, study efficiency, conscientiousness, problematic use, social media

Introduction

This paper focuses on study efficiency, a little studied factor related to university student retention (Roberts et al., 2011) and student outcomes (Rasch & Schnotz, 2009). Much of the previous research on student outcomes examines institutional commitment and adjustment (Credé & Niehorster, 2012), but little is known about study efficiency, which can be defined as a student's perception of the learning outcomes they achieve, relative to the time they devote to learning activities. Given the task switching costs that have been identified when students use different media whilst studying (Rosen et al., 2013) and the potential impact of this on study efficiency and hence student outcomes (Rasch & Schnotz, 2009), in this paper we address the previous lack of research and investigate perceived study efficiency in the context of social media use, specifically YouTube.

YouTube is widely used for entertainment and to obtain information, and is a valuable learning resource for university students (Orús et al., 2016). YouTube can play many roles in a student’s life; for example, Moghavvemi et al. (2017) identified entertainment, maintaining relationships, academic learning, and product enquiry as reasons for use by students. Motivations for YouTube use can be considered from a uses and gratifications perspective (Katz et al., 1973), which argues that users make reasoned choices about use of media to gratify particular needs, such as need for information or entertainment. Studies of social media use have identified that different motivations for use, such as meeting learning needs and uses associated with entertainment, escape, and socialising can affect student outcomes differently (Basak & Calisir, 2015; Klobas et al., 2018). Given these different motivations have previously been considered relevant to student use of social media (Klobas et al., 2018; Throuvala et al., 2019), this paper reports on the effects of three motivations for YouTube use: use for learning, use for entertainment (i.e., to experience a pleasurable response), and use for escape (i.e., to forget or get away from study or everyday life).

Time distortion is a form of perceptual distortion in which time appears to pass either more rapidly or more slowly. In this study, time distortion refers to student perceptions of time passing quickly whilst using YouTube. We argue that time distortion associated with social media use plays a mediating role between use motivation and perceived study efficiency, thus helping to account for conflicting results in previous research about how time distortion when using social media use can affect student outcomes. For example, studies with a narrower focus on use in learning tend to report benefits (e.g., Orús et al., 2016), whereas broader studies where use has multiple motivations have reported some negative outcomes (e.g., Klobas et al., 2018; Wohn & LaRose, 2014).

Personality has been shown to play a role in problematic use of social media (Griffiths, 2013; van der Aa et al., 2009), and in compulsive use of YouTube by university students (Klobas et al., 2018). It is therefore important to consider the influence of personality on other aspects and consequences of social media use by students, including time distortion and perceived study efficiency.

This study therefore addressed the research question: When is time distortion in YouTube use positive or negative for university students? We explored how the time distortion that students experience while using YouTube influences their perceived study efficiency by considering whether the motivation for YouTube use is for learning purposes or for entertainment or escape, and whether personality plays a role. Given previous research showing differences in time distortion (Lin et al., 2015) and academic performance (Glass et al., 2014; Turel & Qahri-Saremi, 2016) between problematic and non-problematic social media users, this study also investigated whether YouTube use behaviour moderates the effects of personality and use motivation on time distortion and perceived study efficiency by exploring three patterns of YouTube usage: occasional, regular, and problematic.

Conceptual framework

Study efficiency

Study or learning efficiency is a component of learning effectiveness (Liaw, 2008) and a contributor to learning outcomes (Rasch & Schnotz, 2009). It has been defined as the perception that students form based on the outcomes they achieve given the time they invest (Smith et al., 2015). This is how we have considered it in this paper, where we define perceived study efficiency as a student's perception of the learning outcomes they achieve relative to the time they devote to learning activities.

Smith et al. (2015) noted a lack of research on study efficiency. Much of the existing research has examined whether different kinds of Internet-based learning influence efficiency. Cook et al. (2010) provided a meta-analysis of this research, concluding that it was not possible to draw generalisable conclusions because of the range of types of course and contexts. Recent research on multitasking during online media use for educational purposes has also touched on questions of study efficiency by examining time use and cognitive load (e.g., Bellur et al., 2015; Dönmez & Akbulut, 2021). Bellur et al. (2015) found that students who multitasked spent more time studying out of class, concluding that multitasking contributes to inefficient study habits. Similarly, in an experiment conducted by Dönmez and Akbulut (2021), when students watching online videos engaged in non-related tasks, either concurrently or subsequent to watching the video, their study efficiency and performance declined. These observations indicate that the other uses students make of technology whilst studying online must be considered when trying to explain study efficiency.

Time distortion

Time distortion is a dissociation between actual and perceived periods of time (Turel & Cavagnaro, 2019). It is generally considered in the context of flow (i.e., a cognitive state characterised by complete immersion in an activity), where time is perceived to pass rapidly when engaged in an enjoyable activity, but it can also be a perception of time going more slowly (Turel & Cavagnaro, 2019). In this study, time distortion refers to student perceptions of time passing quickly whilst using YouTube. Time distortion associated with flow in learning has been shown to increase computational problem solving when using simulation games (Liu et al., 2011) and music student practice efficiency (Miksza & Tan, 2015). Nonetheless, in their study of flow in online learning of physics, Pearce et al. (2005) found that the relationship between flow and learning was not simple. They reported that different students experienced different flow patterns and outcomes. Furthermore, Admiraal et al. (2011) found that flow in an educational history game was associated with increased game performance but not improved learning outcomes.

Use motivation

Communications media use – including social media use – is often explained in terms of use motivations according to the uses and gratifications theory from the field of communications psychology (Rubin, 2009). Users are assumed to have reasons for using a communications medium. Use of the medium results in outcomes which, if they match the user's reasons, are said to gratify them. A user's reasons to use a communication medium to obtain gratification are called use motivations. Use motivations vary with medium, users, and situations of use (Rubin, 2009).

Social media use studies have compared the effects of different use motivations on student outcomes. Commonly studied use motivations in this body of research are: learning use motivation, entertainment use motivation, and escape use motivation. Learning use motivation is motivation to view, listen to or interact with social media content in order to gain factual information, learn a skill, or meet the requirements of a formal course of study (Klobas et al., 2018). Motivation to use social media for enjoyment is described as entertainment motivation, whilst escape use motivation is motivation to use social media to escape from everyday life or concerns (Smock et al., 2011). Use motivations are not mutually exclusive, so it is possible to use a single medium to obtain several gratifications simultaneously, for example, watching an educational YouTube video that entertains, informs, and takes your mind away from everyday concerns.

Comparative studies of Facebook use by students have found that entertainment use motivation has a stronger effect than escape use motivation on time spent on Facebook (Smock et al., 2011) and a stronger effect than learning use motivation on intention to continue using Facebook (Basak & Calisir, 2015). Entertainment use motivation is also associated more strongly than learning use motivation with compulsive YouTube use (Klobas et al., 2018). This is a problem when student use for entertainment is more prevalent than use for learning as observed by Moghavvemi et al. (2017).

Use motivation and time distortion

Time distortion when using the Internet is greater when it is used for entertainment than for task-oriented purposes (Novak et al., 2000). For example, even when YouTube use is intended to be for learning purposes, following links from one video to another can lead to initially unintended use for entertainment and losing track of time (Klobas et al., 2019). Extending this observation to student viewing of online videos, it is possible that time distortion reflects differences in student motivations for use. This notion is captured and extended in the following set of hypotheses:

H1. Students' experience of time distortion in YouTube use varies with their motivation for using YouTube.

More specifically, as greater attention in online learning can be associated with greater time distortion (Kirschner & Karpinski, 2010), if the motivation for YouTube use is learning, then stronger motivation to use YouTube for learning should increase the time distortion that students experience. Therefore, we hypothesised that:

H1a. Stronger motivation to use YouTube for learning increases student experience of time distortion.

The motivation to game to escape life is well established (Király et al., 2017; Larche & Dixon, 2021), and time distortion whilst gaming has been shown to be achieved by those with an escape motivation (Larche & Dixon, 2021; Liu & Chang, 2016). Consistent with this, students who have an escape motivation for using YouTube should experience greater time distortion as their escape motivation increases:

H1b. Student experience of time distortion increases with the strength of their motivation to use YouTube for escape.

Similarly, the time distortion associated with flow has been shown to increase when entertainment is the motive for watching live-streams via social media sites (Chen & Lin, 2018) and when users are gaming for entertainment (Liu & Chang, 2016). Therefore, we proposed that:

H1c. Student experience of time distortion increases with the strength of their motivation to use YouTube for entertainment.

The extent of increase in time distortion is likely to vary depending on use motivation. Time distortion associated with learning use can be expected to be lower than that associated with entertainment use, given the finding from Novak et al. (2000). It is also possible that time distortion associated with escape use is lower than that associated with entertainment use, consistent with Liu and Chang (2016)'s observation that entertainment motivation in online gaming had a slightly stronger effect on flow than escape did. Therefore, we hypothesised that:

H1d. The effect of motivation to use YouTube for learning on student experience of time distortion is less than that of motivation to use YouTube for escape or entertainment.

Time distortion and study efficiency

There have been conflicting results about how time distortion associated with social media use affects students. Earlier studies have tended to focus on either potential benefits (e.g., Hamari et al., 2016; Liu et al., 2011) or potential adverse effects (e.g., Rosen et al., 2013; Turel & Qahri-Saremi, 2016). While Miksza and Tan (2015) found a strong correlation between flow and music practice efficiency, they considered only the flow achieved when doing a specific learning activity. Other authors have reflected in passing on efficient use of time when explaining other outcomes from social media use. Wohn and LaRose (2014) noted that increased time spent using Facebook was associated with lower academic performance and Klobas et al. (2018) observed that uncontrolled, compulsive YouTube use resulted in lower academic motivation. On the basis of these observations, the Moghavvemi et al. (2017) finding that non-learning motivations dominated student YouTube use, and the differences in strength of time distortion by use motivation expressed in H1, we argue that time distortion when using YouTube will lead to reduced, rather than increased, perceived study efficiency:

H2. Time distortion has a negative effect on perceived study efficiency.

Personality effects

Some dimensions of personality have been shown to contribute to problematic use of social media (Griffiths, 2013; van der Aa et al., 2009), and conscientiousness is especially relevant to student outcomes.

Conscientiousness – a person's self-discipline and focus on achievement (Biderman et al., 2008) –was of particular interest in our study because of its strong association with student adjustment to university study (Credé & Niehorster, 2012) and academic performance (Biderman et al., 2008). Conscientiousness is associated with study efficiency (Kelly & Johnson, 2005) and conscientious students spend more time studying (Biderman et al., 2008). Conscientiousness is also associated with the efficiency of multitasking, possibly as a result of more effective strategies for coordination of multiple actions (Stock & Beste, 2015); this might also be the case when students use YouTube for multiple purposes. Therefore, we hypothesised that:

H3. Perceived study efficiency among student users of YouTube increases with conscientiousness.

Conscientiousness might also affect study efficiency through time distortion, although the potential for such an effect is less clear. Several studies of propensity to experience flow in everyday life have found a positive association between conscientiousness and overall proneness to flow. Ullén et al. (2012) argued that this is consistent with conscientiousness being related to other factors linked to proneness to flow, notably active problem coping. However, Ross and Keiser (2014) found little relationship between conscientiousness and time distortion, reasoning that the role of personality is likely to vary with the particular activity that a person is undertaking. In this study of YouTube use, we argued that students who are more conscientious will experience less time distortion and proposed that:

H4. Students' experience of time distortion in YouTube use is reduced by conscientiousness.

Moderating effects of patterns of YouTube use

To this point, we have noted the ambiguous results of research on time distortion and student outcomes and discussed the potential for use motivation and conscientiousness to have different effects on these outcomes of student use of YouTube. A large body of literature has also considered the effect of social media use behaviours on a variety of outcomes, yet despite more than a decade of debate, there is no accepted ontology of Internet use by extent of use (time spent, frequency of login, length of session), object of use (Internet, social media, Facebook, YouTube), function (viewing, contributing, gaming, gambling), or psychological or psychiatric disorder (non-problematic, habitual, problematic, addictive, internet use disorder). Much of this literature has been concerned with symptomatic patterns of use that signal addictive use or, using the World Health Organization's (2018) internal classification of diseases, internet use disorder (Griffiths, 2020). Observed differences between problematic and non-problematic social media users in time distortion (Lin et al., 2015) and academic performance (Glass et al., 2014; Turel & Qahri-Saremi, 2016) were considered sufficiently important for YouTube use behaviour to be taken into account in this research. In order to examine the effects of use behaviours in terms of extent as well as propensity for psychological disorder, a summary variable was needed. In this paper, the summary variable is described as pattern of YouTube use (use pattern in short) to emphasise that it defines a pattern of YouTube use behaviours, combining information about extent of use with propensity for psychological disorder.

We proposed that the pattern of YouTube use moderates the strength of all the relationships hypothesised to this point (H1 to H4). In other words, we expected to see differences in the strength, and perhaps the direction, of the hypothesised effects, depending on the student's pattern of YouTube use, including but not limited to whether it could be considered indicative of a disorder or not. We therefore hypothesised that:

H5. Pattern of YouTube use moderates the effects of personality and use motivation on time distortion and perceived study efficiency.

Research model

Figure 1 summarises the proposed effects of personality and use motivation on student YouTube users' perception of time and its role in determining perceived study efficiency.

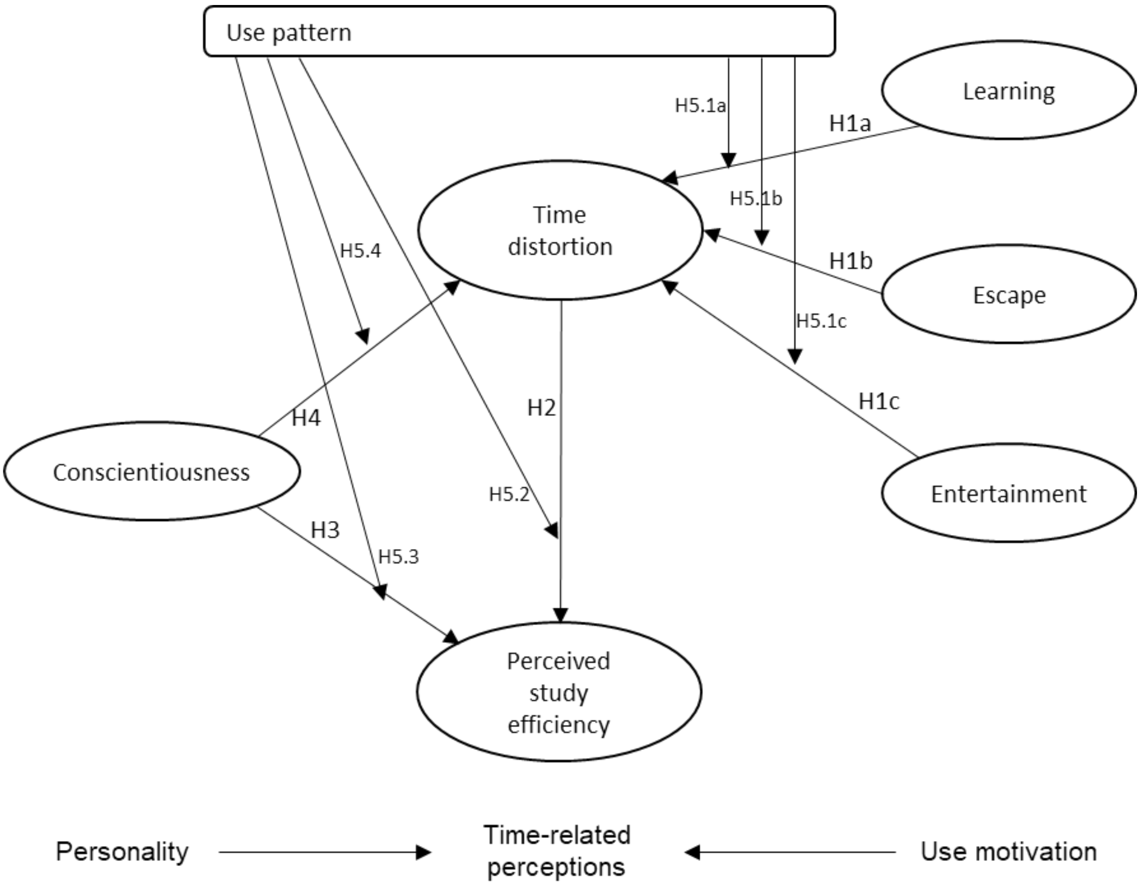

Figure 1. Research model: Hypothesised effects of personality and use motivation on students' time-related perceptions

Method

A dataset drawn from a survey of YouTube use and student well-being was used in this study. Human research ethics approval was obtained from an Australian university for use of this dataset as secondary data (Project No. 2017/232). Hypotheses were tested through SEM in AMOS.

Data

The dataset contained survey responses from 792 students at a research university in Malaysia. It included demographic information about the students' self-reported YouTube usage (frequency of use and session length); scores on established measures of perceived study efficiency (Wohn & LaRose, 2014); perceived time distortion (Novak et al., 2000); personality (John & Srivastava, 1999); uses and motivation for YouTube use (Kaye, 1998, with adaptations for students from Klobas et al. 2018); and items from established Internet use diagnostic tests adapted to YouTube use (Wohn & LaRose, 2014; Young, 1998). The file had already been cleaned for response bias, duplicates, and other identifiable sources of error. In addition, six outliers – identified by calculating their Mahlanobis distance from students with the same YouTube use pattern on all variables in the analysis – were removed.

Measurement

Perceived study efficiency was measured using the time and effort items in Wohn and LaRose’s (2014) academic performance scale: "I do not do well academically considering effort" (reverse) and "I do not use study time efficiently" (reverse). Time distortion was measured with Novak et al.'s (2000) 2-item scale adapted for YouTube use: "Time goes by very quickly when I am using YouTube" and "When I use YouTube, I lose track of time". Learning use motivation was measured with four items adapted by Klobas et al. (2018) from Kaye (1998) to measure student motivation to use YouTube for learning: "I use YouTube" … (1) "to learn about the courses that I am involved in", (2) "to learn how to solve problems", (3) "to get answers for some questions that I have", and (4) "to learn new things". Escape use motivation used the two student-relevant of three items from Kaye (1998) adapted to YouTube use: "I use YouTube " … (1) "so I can forget about study, work or other things", and (2) "so I can get away from what I’m doing". Motivation to use YouTube for entertainment was measured with three items adapted from Kaye (1998): "I use YouTube because” … (1) “it's exciting", (2) "it's thrilling", and (3) "it amuses me". Conscientiousness was a single score, measured according to the Big 5 personality scale of John and Srivastava (1999).

Measurement model quality was tested with confirmatory factor analysis in AMOS. Because the test of H5 required comparison of path coefficients for different use pattern groups, a common measurement model was required. Reliability and validity statistics for this model are shown in Table 1. The measurement model met recommended criteria for reliability (composite reliability was above .7 and average variance extracted was above .5 for all composite latent variables). All variables met the distribution requirements for covariance-based modelling (neither skew nor kurtosis was above |1|). All regression weights were significant with p < .001 and discriminant validity met the Fornell-Larcker criterion as the square root of average variance explained for each composite variable exceeded the correlation between each variable and all others in the model. The model also met common criteria for fit: χ^2 = 140.7, df = 64, p < .001/df = 2.2, CFI = .98, RMR = .035, RMSEA = .039 with p (close) = .99.

Table 1
Reliability and validity statistics, measurement model

Variable	CR	AVE	PStE	TD	CNSC	Learn	Esc	Ent
Perceived study efficiency (PStE)	.73	.58	**.76**					
Time distortion (TD)	.74	.59	-.44	**.77**				
Conscientiousness (CNSC)[a]		1.00	.45	-.23	**1.00**			
Learning use motivation (Learn)	.87	.63	.01	.09	.04	**.79**		
Escape use motivation (Esc)	.80	.67	.25	.34	-.16	-.06	**.82**	
Entertainment use motivation (Ent)	.86	.67	.15	.34	-.03	.29	.29	**.82**

Note. CR = composite reliability; AVE = average variance explained. Items in bold on the diagonal are the square root of AVE. Correlations appear below the diagonal. [a] CNSC has no CR because it is a single item score.

A single moderating variable for the test of differences by use pattern (H5) was developed with SPSS two-step cluster analysis. Input variables were login frequency, session length and scores on two diagnostic scales adapted to YouTube use (Wohn & LaRose's (2014) habitual use scale and Young's (1998) short Internet Addiction Scale). After inspecting the distributions of the variables, each was collapsed to binary form: (1) frequency of use to more than once a day versus once a day or less, (2) session length to less than 2 hours versus 2 hours or more, and (3) habitual use to non-habitual (3 or less on the 5-point scale) versus habitual (above 3). Scores on Young's addiction scale were collapsed using a median split to distinguish between students with little or no risk of addiction (below the median) and those at risk of addiction. These transformations permitted each variable to enter the analysis with a similar weight, avoiding dominance by variables with wider distributions. Good fit (average silhouette measure of separation and cohesion = .6) was obtained with a 3-cluster model containing easily interpreted clusters large enough to support multi-group SEM. Each cluster was interpreted as a use pattern (Table 2): occasional users (uses YouTube only occasionally in short sessions, neither habitual nor at risk of addiction), regular (habitual use, with low risk of addiction), and problematic (habitual use with high risk of addiction, frequent login, and long sessions).

Table 2
Use patterns obtained from cluster analysis of summarised usage metrics

	All respondents		Use pattern					
			Occasional		Regular		Problematic	
	n	%	*n*	%	*N*	%	*n*	%
Cluster size (% of total)	792	100%	324	40.9%	232	29.3%	236	29.8%
Logs in more than once a day	199	25.1%	0	0%	0	0.0%	199	84.3%
Spends 2 hours or more in session	102	12.9%	0	0%	0	0.0%	102	43.2%
Habitual user	365	45.7%	0	0%	194	83.6%	171	72.5%
At risk of addiction	305	25.2%	0	0%	120	51.7%	100	42.4%

Hypothesis tests

Hypotheses 1 to 4 were tested on the pooled data set (all groups) using AMOS SEM. H5 was tested with multi-group AMOS SEM. The measurement model was constrained to be equal for all groups to allow valid comparison of the hypothesised group differences (H5). This approach was supported by group comparison statistics which showed that the measurement constrained model provides significantly improved fit over an unconstrained model (p = .02) while constraining the structural coefficients does not significantly improve fit over the measurement constrained model (p = .052). In all tests, use motivations were permitted to be correlated for analytical purposes and the error variance for latent variables measured with two items was seeded with the AVE reported in Table 1. Interpretation of effect sizes follows Cohen (1988) - η^2: .01 (small), .06 (medium), .14 (large); r: .1 (small), .3 (medium), .5 (large).

Findings

Descriptive statistics

Table 3 shows the sample is 65.4% female, 84.5% aged 20 to 25, and 91.9% undergraduate. This distribution was consistent with the higher numbers of females at the university at the time of the study, but somewhat over-representative of young undergraduates. Frequency of YouTube use ranged from less than once a week (20.1%) to several times a day (25.1%), typically with sessions lasting less than 2 hours (87.1%). Table 2 shows that about 40% of respondents were occasional users, 30% regular, and 30% problematic.

Table 3
Sample characteristics

Characteristic	*n*	%
Gender		
Female	518	65.4
Male	274	34.6
Age		
Under 20	64	8.1
20 to 25	669	84.5
Over 25	59	7.4
Level of study		
Undergraduate	728	91.9
Postgraduate	64	8.1
Frequency of YouTube use		
Less than once a week	159	20.1
Once a week or more	434	54.8
More than once a day	199	25.1
Length of session		
< 30 minutes	363	45.8
> 30 minutes and < 2 hours	327	41.3
>/= 2 hours	102	12.9

Scores on all but one of the variables in the model differed by use pattern, as shown in Table 4. Learning use motivation was high (3.9 on the 5-point scale), regardless of pattern of use. Escape use motivation and entertainment use motivation were lower for occasional YouTube users than for regular and problematic users (medium effects, η^2 = .08, .09, respectively). Occasional and regular users were more conscientious than problematic users, although the effect was small (η^2 = .02). Occasional users also reported lower time distortion than regular users who, in turn, reported lower time distortion than problematic users (medium-large effect, η^2 = .13). Occasional users reported positive perceived study efficiency on average, while regular and problematic users reported negative perceived study efficiency, although the difference was small (η^2 = .03).

Table 4
Comparison of means by use pattern

	All	Use pattern			Differences[a]				
		O	R	P	*F*	*P*	η^2	Contrasts[b]	*p*
Perceived study efficiency	2.9	3.1	2.8	2.8	13.6	<.001	.03	O > [R, P]	<.001
Time distortion	3.5	3.1	3.6	3.8	57.8	<.001	.13	O < R < P	<.001
Conscientiousness	3.1	3.2	3.1	3.0	7.9	<.001	.02	[O, R] > P	<.001
Learning use motivation	3.9	3.9	3.9	3.9	0.5	.6	.00	[O, R, P]	.6
Escape use motivation	3.0	2.7	3.2	3.3	33.1	<.001	.08	O < [R, P]	<.001
Entertainment use motivation	3.6	3.3	3.7	3.8	39.8	<.001	.09	O < [R, P]	<.001

Note. O = occasional; R = regular; P = problematic. Means were approximated as the arithmetic mean of contributing items. [a] *F* tests from one-way ANOVA, all *df* = 2, 789. [b] Bivariate differences. Bracketed group scores are not significantly different.

Hypothesis tests

The hypothesised research model met fit criteria for the pooled sample and when separated by group. Fit scores for the pooled sample were: $\chi^2 = 171.95$, $df = 72$, p < .001, $\chi^2/df = 2.39$, CFI = .98, RMR = .04, RMSEA = .04 with *p* (close) = .95. Multi-group model fit was: $\chi^2 = 380.59$, $df = 232$, $p < .001$, $\chi^2/df = 1.64$, CFI = .96, RMR = .06, RMSEA = .03 with *p* (close) = 1.00.

Table 5 provides the results of hypothesis tests H1 to H4. Standardised coefficients are reported to allow comparison of effect sizes within use groups. All hypotheses were supported except the effect of learning use motivation on perceived time distortion (H1a). The average effects for the whole sample masked distinct differences in effects within the different use pattern groups.

Table 5
Hypothesised effects, whole sample and by use pattern (standardised coefficients)

Effects on:	All	Occasional	Regular	Problematic	Supported
Time distortion					
H1a: Learning use motivation	.03	.04	.10	.05	N
H1b: Escape use motivation	.22***	.17*	.28**	.10	Y
H1c: Entertainment use motivation	.26***	.17*	.11	.24**	Y
H4: Conscientiousness	-.18***	-.15*	-.05	-.25**	Y
Variance explained	.19	.09	.12	.15	
Perceived study efficiency					
H2: Time distortion	-.40***	-.26***	-.44***	-.50***	Y
H3: Conscientiousness					Y
Direct effect	.39***	.51***	.29***	.35***	
Total effect[a]	.46***	.55***	.29***	.48***	
Variance explained	.36	.36	.29	.46	

Note. [a] Total effect deemed significant on the basis of the significance of the direct effect and indirect effect through time distortion. ***$p < .001$, **$p < .01$, *$p < .05$

Escape use motivation (H1b) and entertainment use motivation (H1c) both had a similar effect on time distortion among occasional users, whilst escape use motivation had almost double the effect of entertainment use motivation for regular users and, conversely, entertainment use motivation had more than twice the effect on time distortion as escape use motivation among problematic users. Stronger conscientiousness was associated with a decrease in perceived time distortion (H4) in the pooled sample, although it had no effect for regular users whilst a similar effect to that of entertainment use motivation for occasional and problematic users. Together, use motivation and conscientiousness explained only small amounts of variance in perceived time distortion (19% for the pooled sample, and as low as 9% for occasional users).

Larger differences were seen in the hypothesised effects of time distortion (H2) and conscientiousness (H3) on perceived study efficiency. Together, these variables explained 36% of the variance in perceived study efficiency in the pooled sample, and between 29% (regular users) and 46% (problematic users) for the different use pattern groups. Across the pooled sample, the direct effects of time distortion and conscientiousness were similar, that is, the negative effect of time distortion on perceived study efficiency was counteracted by the positive effect of conscientiousness. However, the size of the compensatory effect differed by use pattern. For occasional users, the positive effect of conscientiousness was about twice the negative effect of time distortion. For regular users, the negative effect of time distortion outweighed the positive effect of conscientiousness. For problematic users, the effects were of similar magnitude.

Table 6 compares the effects across use pattern groups. The effects of use motivations on time distortion were similar for all groups. The negative effect of time distortion on perceived study efficiency was lower for occasional users than regular and problematic users, and the positive effect of conscientiousness on perceived study efficiency was higher for occasional users than regular users.

Table 6
Comparisons between effects by YouTube use group (unstandardised coefficients)

	Use pattern			
Effect on:	Occasional	Regular	Problematic	Diff (H5)
Time distortion				
H1a: Learning use motivation	0.04ns	0.10ns	0.05ns	nsd
	(0.08)	(0.08)	(0.08)	
H1b: Escape use motivation	0.14*	0.23**	.08ns	nsd
	(0.06)	(0.07)	(0.07)	
H1c: Entertainment use motivation	0.18*	0.12ns	.28**	nsd
	(0.03)	(0.11)	(0.10)	
H4: Conscientiousness	-0.26*	-0.08ns	-0.42***	|R| < |P|
	(0.11)	(0.12)	(0.12)	
Perceived study efficiency				
H2: Time distortion	-0.31***	-0.49***	-0.64***	|O| < [|R|, |P|]
	(0.08)	(0.09)	(0.09)	
H3: Conscientiousness				
Direct effect	1.04***	0.53***	0.77***	O > R
	(0.12)	(0.13)	(0.14)	
Total effect[a]	1.12***	0.58***	1.04***	[O, P] > R
H5: Effects vary by user behaviour	See last column			

Note. Standard error in brackets under each effect. [a] Total effect deemed significant on the basis of the significance of the direct effect and indirect effect through time distortion. ***$p < .001$; **$p < .01$; *$p < .05$

Discussion

This research addressed the question: *When is time distortion in YouTube use positive or negative for university students?* and posited that time distortion mediates between motivation for YouTube use and perceived study efficiency, assuming that different use motivations are associated with different experiences of time distortion and these different effects carry through to perceived study efficiency. To develop a more nuanced answer to our question, we took account of personality (specifically, the trait of conscientiousness) and pattern of YouTube use, proposing that they affect time distortion and perceived study efficiency.

As expected, time distortion mediated between use motivation and perceived study efficiency: stronger motivations to use YouTube for entertainment (H1c) and escape (H1b) were associated with stronger experience of time distortion (H1), and time distortion had a negative effect on perceived study efficiency (H2). This observation extends the domains in which time distortion mediates between use motivation and performance beyond live-streaming and gaming (Chen & Lin, 2018; Larche & Dixon, 2021) to YouTube.

The effects on time distortion of the three use motivations varied as hypothesised (H1d). Entertainment motivation had the strongest effect, followed by escape motivation. Learning motivation (H1a) had no significant effect. This is consistent with studies of other online environments where stronger time distortion was observed when use was for entertainment and escape (Larche & Dixon, 2021; Novak et al., 2000). That learning motivation to use YouTube had no effect on time distortion was unexpected, given other studies have found that students who show greater attention whilst learning online experience greater time distortion (Kirschner & Karpinski, 2010), however, learning motivation was high in this study, and there may have been too little variation to identify an effect. More research is still needed to understand the complex relationships between media-assisted learning, perceived time distortion and flow observed by Pearce et al. (2005) and Admiraal et al. (2011).

Moghavvemi et al. (2017) cautioned teachers to beware of the potential for students' attention to be diverted from recommended learning videos to entertainment use of YouTube, but the results of our study indicate that this might not be as great a problem as they thought. Further research is needed to better understand student attention and distraction as students watch recommended videos, including how entertaining learning materials might satisfy both learning and entertainment needs.

Turning to personality, it was not surprising that increased conscientiousness was associated with increased perceived study efficiency (H3) given earlier observations that more conscientious students study with greater efficiency (Kelly & Johnson, 2005) and employ strategies that make them more efficient (Stock & Beste, 2015). Furthermore, among the students in this study, greater conscientiousness was associated with less time distortion when using YouTube (H4). This finding is in contrast to studies that reported a positive association between conscientiousness and proneness to flow in everyday life (Ross & Keiser, 2014; Ullén et al., 2012), but consistent with Ross and Keiser (2014)'s note that the relationship between personality and time distortion likely depends on the specific activities studied. Hence, we argue that more conscientious students experience less time distortion in YouTube use for study purposes because of their self-discipline and ability to maintain clear goals.

When YouTube use pattern was taken into account (H5), we observed differences in the effects of conscientiousness on time distortion and of time distortion on perceived study efficiency, but there were no differences in the effect of use motivation on time distortion between occasional, regular, and problematic users. Figure 2 shows that problematic users reported higher levels of time distortion and lower perceived study efficiency than occasional users, consistent with earlier research showing differences between problematic and non-problematic digital media use in time distortion (Lin et al., 2015) and academic performance (Glass et al., 2014; Turel & Qahri-Saremi, 2016).

The detail in Figure 2 provides a more nuanced explanation of how differences between problematic users and others come about. Firstly, the lack of differences in the effect of use motivation on time distortion shows that one reason time distortion was highest among problematic users was that they were strongly motivated to use YouTube for escape and entertainment. At the same time, conscientiousness offered stronger protection from time distortion for problematic users than for regular users. Even so, conscientiousness just countered the effect of entertainment motivation on time distortion for problematic users. Furthermore, neither conscientiousness nor entertainment use motivation had any effect on time distortion for regular users. It was as if regular users consciously used YouTube for escape, that is, escape use was a habit they could control.

When looking at the differences in perceived study efficiency, occasional users stood out from the others. Not only was their time distortion lower, but their perceived study efficiency was higher and the effect of time distortion on perceived study efficiency was weaker. Conscientiousness had a strong positive effect on perceived study efficiency for occasional users, and a weaker effect for regular users. Taken together, these observations show that understanding a student's use pattern adds to knowledge of the motivational and personality effects of YouTube use on student outcomes.

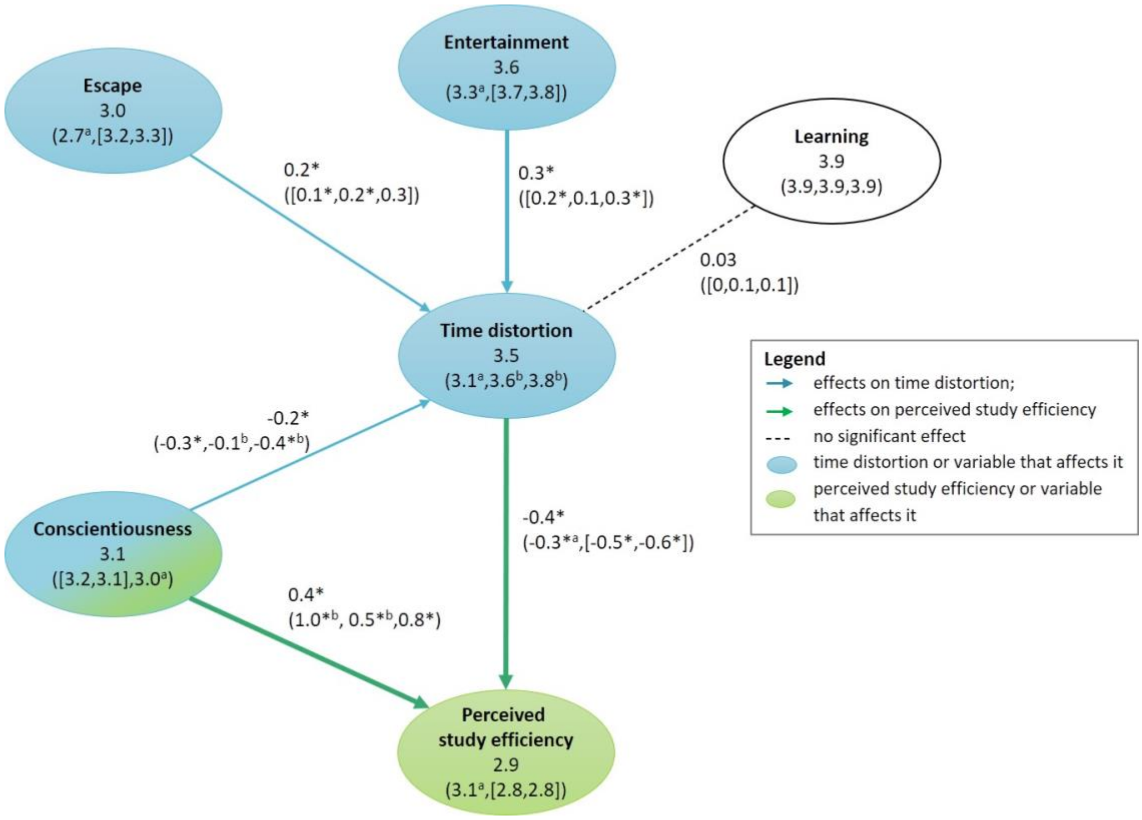

Figure 2. Similarities and differences in use motivation, conscientiousness, time distortion, and perceived study efficiency for students with different patterns of YouTube use

Note. Values directly under variable names are pooled sample means. Means for use pattern groups are in brackets below the pooled mean (occasional, regular, problematic). Group means within square brackets are significantly different from the other group means but not significantly different from one another.

Values on arrows are standardised pooled effects. They appear above unstandardised use pattern group effects in brackets (occasional, regular, problematic). Group effects within square brackets are significantly different from the other group effects but not significantly different from one another. Arrow width represents the strength of the pooled effect: wider arrows indicate stronger effects.

[a] Group value is significantly different from both others. [b] Pair of significantly different groups. *Statistically significant difference. Details in Tables 5 to 6.

Implications

The findings of this study provide insight into how time distortion experienced in student YouTube use mediates the effect of use motivation on perceived study efficiency in the presence of differences in conscientiousness and YouTube use patterns. The findings suggest that the relationships are more complex than previously assumed. Three patterns of YouTube use were identified (occasional, regular, and problematic) and differences in how time distortion and conscientiousness influence perceived study efficiency are associated with these patterns. Further research is needed to understand these differences. Such research might include experiments that seek to reduce time distortion and increase study efficiency by increasing self-discipline and goal-orientation in media use for all students, not just those with high conscientiousness. The different effects of entertainment and escape use motivations on time distortion also indicate that both these use motivations should be considered in future social media use studies.

This research also has practical implications for instructors, students and support staff. Instructors should be mindful of the risks of time distortion and reduced study efficiency when students use YouTube, particularly those who are not conscientious or who have strong motivation to use YouTube for entertainment or escape. Support teams could develop awareness and training programs for university adjustment to help students become more aware of the ways in which YouTube use can affect academic outcomes such as study efficiency and help them to increase self-discipline and goal-orientation.

Conclusion

This research posed the question: When is time distortion in YouTube use a positive or negative for university students? The simplistic answer is that it is always negative; however, both conscientiousness and pattern of use, mitigate this. Conscientious students, who exercise self-discipline and task-focus, as well as occasional users, experience less time distortion in YouTube use and study more efficiently. To better understand student outcomes from YouTube use, we recommend closer attention to students' experiences in use (such as time distortion), personality, and patterns of use for specific learning activities. Future research should develop and test interventions that help students improve their study efficiency in the face of potential distraction from entertainment media, as well as immersive media and platforms such as the proposed Metaverse.

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