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TikTok and cognitive load: the effects of short-form videos on recognition memory

DECLARATION OF AUTHORSHIP:

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Family, friends, and the shoulders of giants.

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Abstract

The rise of short-form videos (SFVs) with the likes of TikTok has generated concerns over their effects on cognition. Previous studies have drawn on theories such as cognitive load and event segmentation to explain how SFVs can be uniquely detrimental to cognitive abilities. However, the current research gap resides in direct comparisons between short and long video formats, as well as investigating TikTok as a form of distraction. Utilizing an old-new recognition test, incorporated with an immediate and delayed recognition test phase, this study measures how task-switching to different distractions: 1) watching TikTok videos 2) watching a continuous YouTube video, and 3) reading an article will impact recognition memory. The results showed that while task-switching to any type of distraction negatively impacts recognition, there was no significant difference in recognition impact between the three types of distractions. This challenges the previous evidence of SFVs being a uniquely detrimental media format, informing us on the wider topic of social media distractions.

1. Introduction

Recent years see the proliferation of ‘social media panic’ in society, leading to terms like the ‘iGeneration’, referring to the new generation’s reliance on social media for identity-formation (Twenge, 2017). Moreover, the rise of short-form videos (SFVs) with the likes of TikTok has caused a new wave of panic over issues of data security, and cognitive impacts surrounding attention, addiction and so on. A panic which culminated with the banning of the TikTok platform by the US congress in April 2024 (McMahon, 2025). However, like many targets of moral panic, there is mixed evidence from scientific literature. On one hand, TikTok can negatively impact long-term attention abilities through its highly personalized algorithms that facilitate addictive behaviour (Chen et al, 2023; Zhao et al, 2021; Qin et al, 2022). On the other hand, SFVs can be a useful tool that enhances learning (Mariappan, 2024). Angga et al (2022) show that school curriculum can be successfully adapted to TikTok formats, leading to improved performance and understanding in students. Evidently, it is pointless to argue over TikTok’s inherent harm or benefit. First, because SFVs’ effects on human cognition vary depending on their utilization. Second, addictive habits extend across social media platforms, including Facebook and Instagram (Ryan et al, 2014; Ponnusamy et al, 2020). Therefore, this study aims to investigate TikTok under more specific situations that are relevant in everyday life. We investigate TikTok as a source of distraction, in the context of other media formats, to determine whether SFVs are truly unique in their influence of cognition.

1.1. *Theoretical framework*

Task switching and cognitive load

It is well established that when individuals switch tasks, the executive function becomes temporarily impaired due to the mental effort caused by a switch. This is termed a ‘switch cost’, marked by extra activation across various brain regions linked to increased working memory processing (Wylie & Allport, 2000; Monsell, 2003). Notable tests like the dual-task paradigm corroborates the existence of a switch cost (Hughes et al, 2014). For example, Muhmenthaler and Meier (2019) studied task-switching’s effect on memory encoding, the process where sensory information is transformed into memory to be stored. In a study phase, one group of participants switched between classifying animals and physical objects, while another group was given single tasks of only classifying animals or only classifying objects. Then, in a test phase, the groups engaged in a recognition task, where

they had to recognize whether an object was previously presented in the study phase or a new object. The findings showed that recognition accuracy significantly degraded in the switch group compared to the repeat group, indicating that the switching of stimuli during presentation can impair encoding processes, leading to worse retrieval.

Importantly, Liefoghe et al's (2008) experiment further suggest that the disruptions of switch costs are not limited to the encoding stage of memory, but also the consolidation stage, when encoded memory is meant to be strengthened. In their study, participants had to recall a list of consonants, while frequently switching to a secondary task of number judgements. For instance, if a number was red, participants judged whether it was larger or smaller than five; if a number was blue, participants judged whether it was odd or even. During testing, one group was given numbers which alternate in colour, while another group was given repeating colours, both groups were then tested on their recall of consonants. Results revealed that the recall accuracy would significantly decrease for the group with alternating colours during the secondary task compared to the repeating colours group. Given that the encoding stage (consonant list) was unmanipulated in both groups, this strongly implies that the act of switching itself generates a cost that can affect the consolidation processes of working memory, even when the stimuli being remembered is unrelated to the task-switching.

The idea of a 'switch cost' coincides strongly with the cognitive load theory (CLT), which posits that the capacity of working memory is limited, so high amounts of mental effort can overload working memory, and hinder cognitive abilities (Sweller, 1988). Over the years, CLT has developed into an all-encompassing theory that is applied to many domains of cognition and behaviour, including task-switching (Paas et al, 2003; Paas et al, 2010). Chis et al's (2023) experiment analysed participants' cognitive load (CL) changes while switching tasks in a simulated search-and-rescue game. During the game, participants had to remember a list of victim location, while organized into a team with different roles (searching, evacuating, healing victims), where some roles entailed more task-switches than others. Each participant was measured on their likelihood of forgetting victims, based statistically on the number of trials it took them to fulfil their missions. The researchers then conducted an analysis using the Adaptive Control of Thought – Rational (ACT-R) model by Anderson (2014), which calculates an individual's CL based on their likelihood of forgetting information *i.e.* higher likelihood of forgetting corresponds to high load. The analysis

confirmed that those who had task-switching roles would often forget more victims, scoring significantly higher on CL compared to low task-switching roles.

Similarly, Thomas et al (2017) conducted a study which measured the changes in subjective CL of nurses during work interruptions. They used Hart and Staveland's (1988) NASA Task Load Index, which measures individuals' subjective perception of workload based on factors like mental or physical demand, emotional frustration *etc.* Thomas and colleague administered the index on nurses and asked them to self-report the amounts of distractions they faced during work. They discovered that although the number of interruptions during worktime did not lead to higher error rates in job performance for nurses, there was a significant positive relationships between the effects of work interruptions and CL. Distractions during work, like switching between unresolved issues, tends to increase the subjective perception of workload and stress in nurses. As such, this study and Chis et al's (2023) research clearly highlight a strong link between task-switching and CL, which is reliably observed in both objective and subjective assessments of load changes during task-switching.

This is highly relevant to social media, because features like push notifications, or instant messaging have introduced a major source of distraction for app users. These features provoke a 'checking behaviour', where users engage in frequent, short durations of phone use throughout the day (Wilcockson et al, 2018). Heitmayer and Lahlou (2021) studied young adult's smartphone usage and reported that checking behaviour can range from 10 minutes every hour, to 1 minute every 5 minutes. Checking behaviour is problematic, as it reinforces a constant demand for task-switching that develops into habitual behaviour, that has bled into academic and work lives (Rosen et al, 2013; Deng et al, 2019). However, based on CLT, the effects of such social media distractions should likely vary depending on how cognitively loading each platform is. The question, thus, is whether TikTok displays a higher cognitive loading capacity? Indeed, there are two accounts of this in current literature.

TikTok and cognitive load

First, according to Lang et al (1999; 2015), the pacing and arousal levels of media formats determine its cognitive loading capacity. In their experiment, participants are tasked with

recognizing televised messages under different conditions of pace (fast, medium and slow delivery), and arousal (cartoons or talk-shows, coded for arousal levels by third parties). They concluded that a significant interaction of pace and arousal exists. Recognition was worst when it was delivered in both fast and highly arousing ways, compared to when it was only fast, or only arousing. Applying this to TikTok, the average video on TikTok range from 30 seconds to 50 seconds (Ceci, 2024), compared to the average length of YouTube videos at 11 minutes (Ceci, 2023). So, as an entertainment platform, TikTok is irrefutably faster paced. Moreover, Su et al (2021) conducted an fMRI analysis of individuals when watching personalized versus non-personalized TikTok feeds. They revealed that there is significantly higher activation of the ventral tegmental area, the reward system of the brain, when scrolling personalized feeds compared to non-personalized feeds. This coincides with the wider evidence that TikTok's personalized algorithm can generate highly stimulating content that facilitates addictive behaviours (Qin et al, 2022). TikTok, therefore, displays both the fast-paced and arousing characteristics of media delivery that increases CL.

Second, the event segmentation theory (EST) posits that memory is encoded via automatic segmentation of information into periods of clear beginnings and ends, termed an 'event' (Kurby & Zacks, 2008). During an 'event boundary', when one event ends, the processing load of memory increases due to the need to encode for a new event, neurologically marked by activation in brain regions like the medial posterior temporal (Speer et al, 2007; Radvansky & Zacks, 2017). This phenomenon was empirically observed with Rinck and Weber's (2003) study, which measured the reading time of participants for literary texts coded for event boundaries. They showed that an increase in reading time specifically occurred after shifts in the narrative, such as a change in protagonist, space, or time. This implies that increases in CL, inferred through slower reading speed, occurs at a new 'event' indicated by narratives shifts. Follow-up studies also observe that by manipulating the number of shifts in a narrative text, reading time and memory for story details will be equally impacted, with more shifts causing slower reading and worse memory for text details (Speer & Zacks, 2005). This concept is highly applicable to TikTok, where its rapidly switching video format should see increase demand for event segmentation.

Paltaratska's (2023) research directly studied EST in the context of TikTok videos through eye-tracking methods. Based on previous evidence, eye behaviour can be reliably used to infer changes in CL (Perkhofer & Lenner, 2019). For example, Wang et al (2014) proposes that eye fixations are highly linked to information processing, so, longer fixation durations strongly indicate more information being processed, and subsequent increase in CL. While the velocity of saccades, the movements between fixations, is also a good indicator of information processing and subsequent CL (Zagermann et al, 2016). Paltaratska compared these eye behaviour data in participants over the course of watching a TikTok video and discovered that CL tends to increase at the end of every video, rather than the rest of the video. Consistent with EST, since the end of TikTok videos constitute 'event boundaries', extra processing load is needed to prepare for a new memory segmentation. Therefore, SFVs can potentially lead to cognitive overload through the saturation of event segmentation demand. Importantly, both the EST and Lang et al's (1999) accounts are not mutually exclusive. Reasonably, we can classify the constant switching format of TikTok, which triggers event segmentation, to be a component of fast-paced stimuli studied by Lang and colleague.

Both accounts give a plausible explanation on how SFVs may be more cognitive loading than other media formats. However, some important clarifications must be stated. First, none of the accounts have directly incorporated task-switching paradigms, which would further inform us how different media formats would function as distractions. Second, the cognitive loading effects of pace and arousal were primarily investigated for the memory encoding stage. That is, Lang et al (1999) highlighted that memory for stimuli became worse when the encoded stimuli themselves were fast-paced and arousing. While many studies have already detailed CL's role in memory encoding (Sherman et al, 2000; Dubravac & Meier, 2022), less research specifically focus on isolating the effects of CL to memory consolidation stages. Thus, it remains to be explored if the properties of SFVs can affect our memory for unrelated stimuli, much like 'switch costs' in task-switching have been found to do so (Liefoghe et al, 2008). Essentially, will the pace and arousal of media formats uniquely affect our memory consolidation processes?

SFVs and other media formats

Chiossi et al (2023) was the first to apply a task-distraction model to study the effects of different media formats on memory. For instance, Twitter may contain fast context-

switching pace, but is primarily text based, so have low arousal. An edited YouTube video has high arousal levels but is slower paced with fewer context-switches. While TikTok is both fast-paced and highly arousing. Their study investigated how task-switching to these distractions impacted people's prospective memory (PM), the ability to recall one's intentions and goals. In their experiment, participants do a simple Lexical Decision (LD) task, where they judge whether a set of letters formed a word or a non-word. Participants were also instructed on a PM task: when a specific word showed up in the LD task, like 'Blue', participants must respond with a specific key on a keyboard. The joint LD and PM tasks was administered before and after a 10-minute distraction. During distraction, individuals were separated into four different task-switching conditions: avoiding screentime, browsing Twitter, watching a single YouTube video, or watching TikTok shorts. Their results revealed that the TikTok distraction group was the only one that showed significant increases in error rates for the PM task. Since PM task error rates have been strongly linked to CL levels (Matos et al, 2020; Hu et al, 2023), it was inferred that SFVs uniquely contributed to PM impairment via cognitive overload.

However, no study to date has evaluated whether similar effects extend to retrospective memory (RM), our ability to retain information of the past. A closely related research was conducted by Li et al (2024), who analysed TikTok as a 'carry-over' effect. Li and colleague tested how experiencing 25 minutes of different activities would impact subsequent encoding of a TV show (BBC's Sherlock). In a 25-minute priming phase, two groups would watch either personalized or random feeds of TikTok, while two groups would watch a continuous video, either related to Sherlock, or an unrelated documentary. Then, all participants would watch 20 minutes of the Sherlock segment, after which they would be tested on a free recall method, where they list down remembered details of the show freely. Their results showed that regardless of personalized or random feeds, watching SFVs led to significantly fewer and less-detailed recall for the show compared to continuous video watchers. Furthermore, like Paltaratskaya (2023), Li and colleague used eye-tracking methods to link SFV's detrimental effects on memory to EST. Eye-tracking results suggested that watching a random TikTok feed, specifically, led to disrupted event segmentation processes. This is surprising, as previous research proposed that watching personalized videos should be more detrimental to cognition, due to their more arousing content that adds to CL (Lang et al, 1999; Su et al, 2021).

While Li et al (2024) contributed much to the understanding of media format's effects on episodic memory, since their study centred around memory encoding, it did not address the research gap of how media formats affect memory consolidation. Whereas Chiossi et al's (2023) study isolated the memory consolidation stage, since distractions were administered in between PM tasks, and successfully reported that SFVs could disrupt PM consolidation. Therefore, this highlights an additional need for Chiossi and colleague's task-distraction method to be applied to RM domains, as it would show how SFVs influence extend to episodic memory consolidation.

1.2. *The present study*

Our study sought to integrate the previous experiments on media formats and task-switching. We focused on the episodic memory component of recognition, which allowed for more flexible assessments of memory with both objective methods like the signal detection theory (SDT) and subjective measurements through confidence ratings (Parks, 1966; Weideman & Kahana, 2016). Drawing inspiration from Chiossi et al's (2023) model, we utilized the established old-new recognition (ONR) test, separated into an immediate and delayed recognition phase, where distractions can be administered between the two phases. Based on the previously explained theories of pace, arousal and EST, we compare how recognition is impacted by task-switching to three different types of media distractions: (1) short videos on TikTok (high load), (2) a continuous YouTube video (moderate load), and (3) a control condition of reading (low load). According to the literature, we expect task-switching to generally degrade recognition due to heightened CL through 'switch-costs'. However, due to SFVs' uniquely cognitive loading properties, we also predict that TikTok use will more severely degrade recognition compared to other media formats. In turn, we make the following hypotheses:

H1: Recognition accuracy and confidence will be significantly worse after a distraction compared to before.

H2: Difference in recognition accuracy and confidence before and after a distraction will be larger for the TikTok condition, compared to the YouTube and reading condition.

2. Materials and Methods

2.1. *Participants*

A G*Power (Faul et al, 2009) analysis revealed that a sample size of 36 was required for our study. We assumed a large effect size would be found ($R^2 = .50$), based on Chiossi et al's (2023) results, while establishing a significance level of .025, a power of .80, and assuming low correlation between variables of $R = .30$. 41 students aged 18+ who were currently studying at the University of St Andrews were recruited via physical and online advertisements. No specific demographics information was attained from the participants. The data of five participants were excluded due to interruptions during the experimental process, leaving a sample size of 36. Informed consent was obtained in accordance with the School of Psychology and Neuroscience Ethics Committee at the University of St Andrews. (Ethics approval code: PS18217; see **Appendix A.**).

Several confounds relevant to our study were screened for. First, healthy participants, defined as those without diagnosed neurological disorders, were recruited to prevent working memory deficits found in conditions like Attention-deficit/hyperactivity disorder (ADHD) from influencing performance (Alderson et al, 2013). Second, to ensure participants' familiarity with TikTok's interface designs and functions, we screened for participants who self-identify as a 'regular' TikTok user, defined as those who use TikTok daily, regardless of time spent on it. This choice also avoids the ethical issues of encouraging TikTok use to non-users. Finally, evidence have linked long-term TikTok addiction to symptoms of memory loss and degraded attention management (Sha & Dong, 2021; Chen et al, 2023), thus, TikTok addiction in participants may be a confound for recognition performance. Participants were assessed on a TikTok addiction questionnaire post-experiment, with the data of those discovered to be 'TikTok addicted' discarded. Our analysis revealed that no participants could be classified as TikTok addicted.

2.2. *Materials*

TikTok Addiction questionnaire

The TikTok addiction questionnaire consists of 20-items that measure the likelihood of TikTok addiction in participants (See **Appendix B.**). It is adapted from Young's (1998)

Internet Addiction Test by substituting references to the ‘internet’ with ‘TikTok’. The adapted version was previously utilised in Su et al’s (2021) study, which showed that the scale can be employed successfully. Responses are recorded in a Likert-scale ranging from 1 (rarely) to 5 (always). The maximum score of the test is 100, with different score threshold indicating severity levels of addiction: Normal usage (0 – 30), mild dependence (31 – 49), moderate addiction (50 – 79), and severe addiction (80-100). For our study, only participants who have scored over 80 was considered as TikTok addicted.

Distractors

TikTok and YouTube videos were chosen as they represent the most mainstream forms of short video and long video social media. However, unlike Chiossi et al (2023), which allocated screen avoidance as the control group, we chose reading as the activity for the control condition. Since we aim to study everyday distractions, it was decided that having a simple task provided more ecological validity compared to inactivity. Based on the theories of pace and arousal, we assumed that a none-switching format like reading would display the lowest cognitive loading capacity. Moreover, the use of academic articles instead of narrative texts should also minimize ‘event boundaries’ caused by narrative features like protagonists, time or space, as established by EST studies (Zwaan et al, 1998; Speer & Zacks, 2005).

Distractions were administered through an iPhone SE (IOS version 18.3), set up with two applications. First, a TikTok app logged into a temporary account created specifically for the study, showing random feeds of TikTok as opposed to personalized feeds. Second, a Google Drive consisting of two folders. A ‘YouTube videos’ folder containing five videos approximately five-minutes in length, taken from various popular educational YouTube channels (For the full list of videos, see **Appendix C**). A ‘Readings’ folder containing five academic articles taken from various journals and focused on general, non-science topics (For full list of readings, see **Appendix D**). The reason we chose not to utilize the YouTube app for long-video watching was mainly to prevent the presence of advertisements which may interfere with CL by introducing a context switch.

Old-New recognition (ONR) test

The ONR test was programmed using MATLAB (The MathWorks Inc., Natick, MA, R2024b) and the Psychophysics Toolbox model (Brainard, 1997). The test was run on a PC provided by the university, with a screen resolution of 1920x1080 pixels. A block of ONR test consists of four phases: encoding, immediate recognition, distraction, and delayed recognition.

In the encoding phase, 60 words were flashed on a white background one-by-one, each lasting for two second. Since previous research has suggested that word similarity can significantly increase likelihood of falsely recognizing a new word as 'old' (Montefinese et al, 2014), the word list used for testing was designed to consist of semantically unrelated, high frequency nouns. In the immediate recognition test phase, 60 probe words were presented: 30 targets (words shown during encoding), and 30 lures (words not shown during encoding). For each given probe, participants were instructed to identify whether it is an 'Old' word by pressing 'B' on a keyboard, or a 'New' word by pressing 'N'. After answering the 'old-new' component, they were prompted to report their confidence level for the recognition on a 3-point scale (1 = low confidence, 2 =medium confidence, 3 =high confidence). In the distraction phase, on-screen instructions prompted participants to access the respective distractors on the phone. The sequence of distractions was randomized for each participant, thus any of the three distractions could be prompted in a given test block. During distraction, a timer began counting down from five minutes. Once finished, participants proceeded to a delayed recognition test phase, sharing an identical process to the immediate test phase, but with 60 additional probes words presented, 30 consisting of previously untested targets, and 30 new lures.

2.3. Design and procedure

The experiment was held in a lab-based setting and takes roughly one hour to complete. In a within-subjects design, participants went through three blocks of the ONR test, each with a distinct five-minute distraction condition (reading, YouTube video, TikTok shorts), presented in randomized sequence. Before testing, each participant was provided with the iPhone and explained the basic information on how to access the distractions. Once the MATLAB program has been set up, instructions for the ONR test were presented, and a short practise stage took place before real testing began. After participants have finished

three blocks of ONR tests, the TikTok addiction questionnaire was administered, the completion of which marks the end of the study.

2.4. Data Analysis

All collected data was analysed using SPSS v27. All statistical tests used are parametric unless stated otherwise. The ONR test incorporates SDT, comprising of four matrices: 'Hits', 'Miss', 'False Alarms', and 'Correct Rejections' (Parks, 1966) (See **Figure 1.**). However, a known issue of signal detection theory in an ONR test is the occurrence of extreme response proportion values, such as a 100% 'Hit' or 'Miss' rates, that would distort calculations of recognition accuracy (Hautus, 1995). Therefore, Snodgrass and Corwin's (1988) correction methods were applied by using their formula, seen in (1) and (2), to calculate each participants' recognition sensitivity (d') and response bias (c). Recognition sensitivity denotes an individual's ability to discriminate between old and new items, with higher values meaning stronger discrimination. Response bias denotes an individual's tendency to classify items as 'old', with negative values indicating more likelihood to do so, while positive values indicate less likelihood to do so. Furthermore, Tekin et al (2021) stated that the confidence-accuracy relationship is more pronounced in 'Hits' than in 'Correct Rejections', where high confidence in 'Hits' usually indicates high accuracy more so than high confidence in 'Correct Rejections'. Thus, confidence ratings were reported based on each participants' average confidence levels for 'Hits' only.

$$d' = Z_{FA} - Z_H \quad (1)$$

$$C = 0.5(Z_{FA} + Z_H) \quad (2)$$

Figure 1.

Signal detection theory components in an ONR test

		Response	
		Old	New
Stimulus	Target	Hit Old item classified as 'old'	Miss Old item classified as 'new'
	Lure	False Alarm New item classified as 'old'	Correct Rejection New item classified as 'new'

3. Results

3.1. Test phase and recognition performance

According to **H1**, we predicted that recognition performance will decrease after distractions. Indeed, average d' and confidence ratings across distraction conditions was worse in the delayed test phase compared to the immediate test phase (see **Table 1**). A 3x2 repeated measures ANOVA confirmed that significant main effects of test phase were present for recognition sensitivity ($F_{(1,35)} = 157.453, p < .001, \eta_p^2 = .818$), as well as confidence ratings ($F_{(1,35)} = .920, p < .001, \eta_p^2 = .375$). Post-hoc paired samples t-tests revealed that for recognition sensitivity, d' became significantly lower in the delayed test phase compared to immediate test phase for reading ($t_{(35)} = 6.994, p < .001$), TikTok ($t_{(35)} = 6.943, p < .001$), and YouTube ($t_{(35)} = 9.197, p < .001$) conditions respectively (**See Figure 2.**). Similar trends were found for recognition confidence, where there were lower confidence ratings in the delayed recognition phase compared to immediate phase for reading ($t_{(35)} = 2.681, p = .006$), TikTok ($t_{(35)} = 4.377, p < .001$) and YouTube ($t_{(35)} = 2.072, p = .023$) conditions respectively (**See Figure 2.**). These results fit with the hypothesis that task-switching to distractions can impair recognition performance.

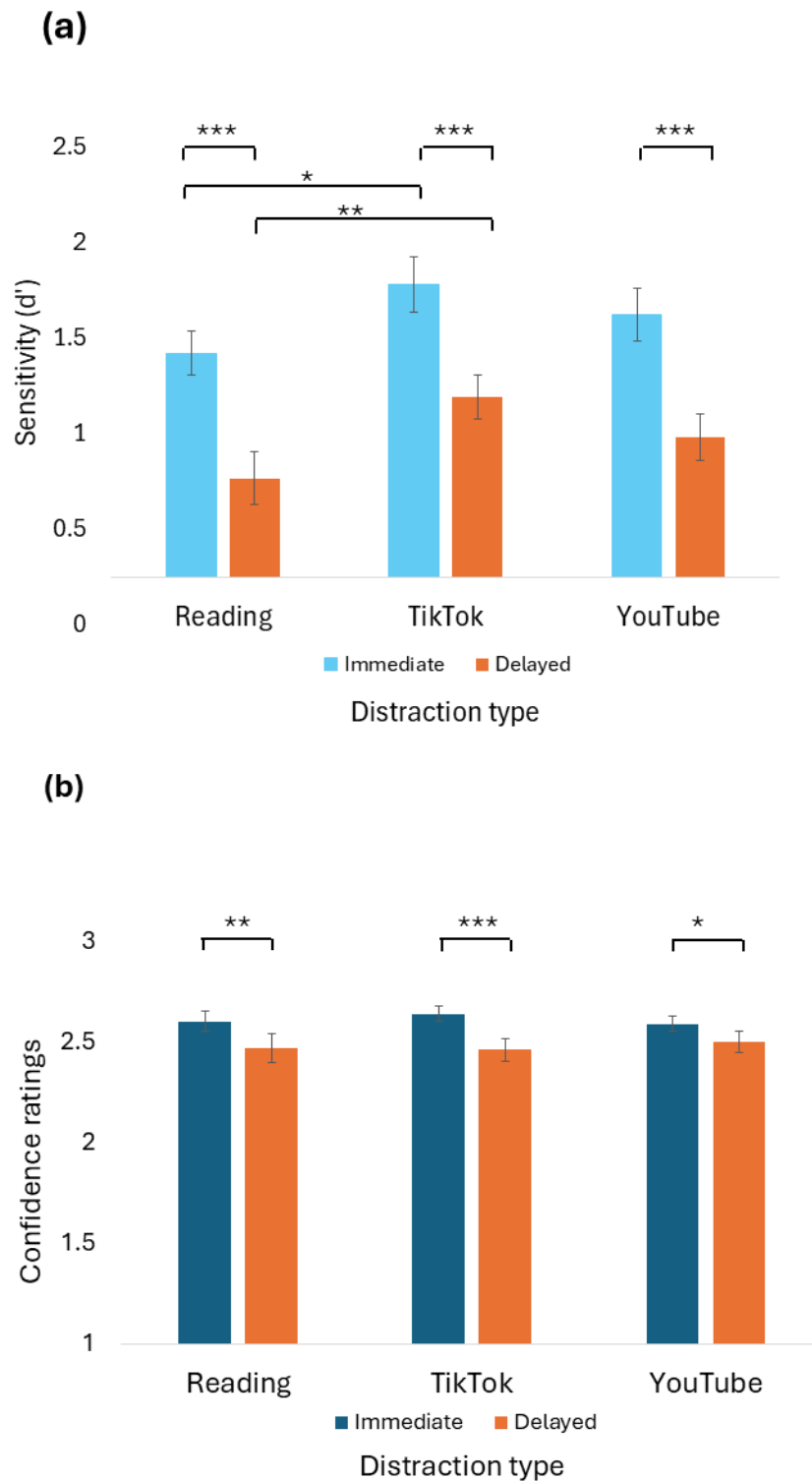
Table 1.

Means and standard deviation for recognition sensitivity (d') and confidence ratings (conf) between immediate and delayed recognition phases across distraction conditions.

Distraction	Immediate recognition				Delayed recognition			
	d'		Conf		d'		Conf	
	M	SD	M	SD	M	SD	M	SD
Reading	1.42	.71	2.60	.30	.77	.83	2.47	.42
TikTok	1.78	.86	2.64	.23	1.19	.70	2.46	.33
YouTube	1.62	.85	2.59	.22	.98	.72	2.50	.32

Figure 2.

Average (a) recognition sensitivity and (b) confidence ratings for immediate and delayed test phases across different distraction conditions. Error bars represent standard errors from the mean. *** $p < .001$, ** $p < .01$, * $p < .05$.



3.2. *Distraction type and recognition performance*

According to **H2**, we predicted that TikTok would uniquely impact recognition performance in a negative way relative to YouTube and reading. A 3x2 repeated measures ANOVA revealed that a main effect of distraction type on recognition sensitivity was indeed present (sphericity assumption violated; Mauchly's test $p = .032$, Greenhouse-Geisser corrections applied) ($F_{(1.691,70)} = 6.927, p = .003, \eta_p^2 = .165$). Bonferroni-corrected pairwise comparisons showed that average d' in the reading condition ($1.09 \pm .74$) was significantly lower than the TikTok condition ($1.47 \pm .73; p = .002$), but there was no significant difference between YouTube condition ($1.30 \pm .75$) and reading nor TikTok conditions (See **Figure 3**). However, no main effects were found for distraction type on confidence ratings ($F_{(2,70)} = .141, p > .05, \eta_p^2 = .004$). The average confidence ratings did not significantly differ across reading ($2.54 \pm .33$), TikTok ($2.56 \pm .25$), and YouTube ($2.54 \pm .24$) conditions. This means that while distraction type impacts recognition sensitivity, it does not affect individuals' confidence in their recognition.

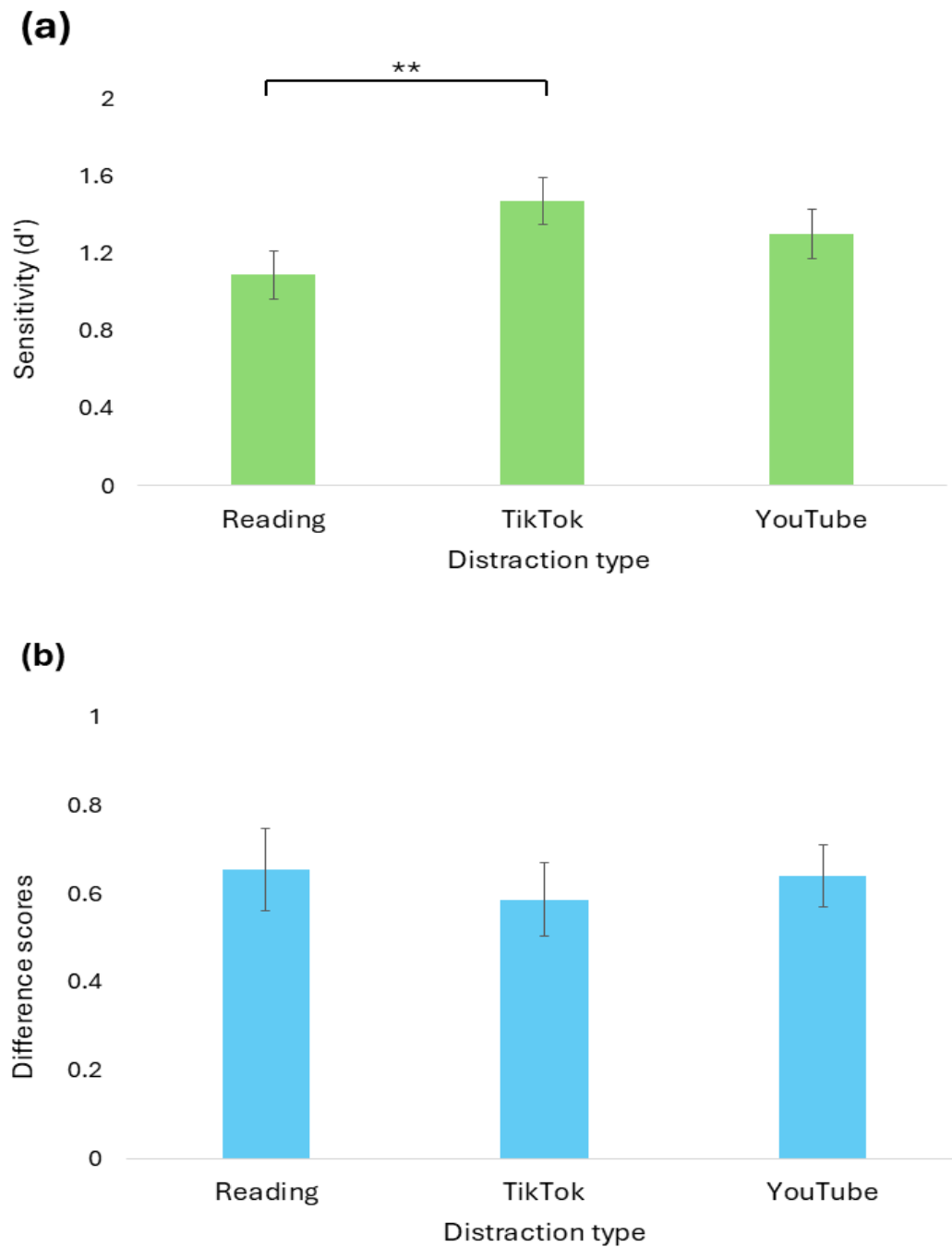
No significant interactions were found between test phase and distraction type for both recognition sensitivity ($F_{(2,70)} = .195, p > .05, \eta_p^2 = .006$) and confidence ratings ($F_{(2,70)} = 1.177, p > .05, \eta_p^2 = .033$). This means that the type of distraction did not influence the changes in performance across immediate and delayed recognition phases. To ascertain this, a difference scores analysis was conducted. First, difference scores were calculated by subtracting the d' between the immediate and delayed test phases for reading, YouTube, and TikTok conditions. Then, a repeated measures ANOVA was run to compare the impact of the three distraction types on recognition sensitivity. The results revealed that there were minimal variations in difference scores between reading ($.655 \pm .56$), TikTok ($.587 \pm .51$), and YouTube ($.641 \pm .42$) conditions. ANOVA concluded there were no significant differences in recognition impact between distractions ($F_{(2,70)} = .195, p > .05, \eta_p^2 = .006$) (See **Figure 3**). Therefore, no evidence was found that TikTok uniquely impacts recognition memory in a negative way.

However, to further investigate the main effects found for distraction type on recognition sensitivity. Two repeated measures ANOVAs were run to compare d' across distraction conditions within immediate and delayed phases separately. Here, an unexpected result

was found, a significant difference between distraction type was present in both the immediate test phase ($F_{(2,70)} = 4.789, p = .011, \eta_p^2 = .120$), as well as the delayed test phase ($F_{(2,70)} = 5.861, p = .004, \eta_p^2 = .143$) (See **Figure 2**). For the immediate test phase, Bonferroni corrected pairwise comparisons show that d' in the reading condition was lower than the TikTok condition, but YouTube condition did not differ with reading nor TikTok (See **Table 1**). Similar trends existed for the delayed test phase, showing lower d' in reading compared to TikTok conditions, and no difference between YouTube and reading nor TikTok conditions (See **Table 1**). Since, the immediate recognition phase should be identical across distraction conditions, the statistical difference found strongly implies the presence of order effects.

Figure 3.

Average (a) overall recognition sensitivity and (b) difference scores between reading, TikTok and YouTube distraction condition. Error bars represent standard errors from the mean. *** $p < .001$, ** $p < .01$, * $p < .05$.



3.3. *Order effect analysis*

We first analysed the frequency distribution of distraction sequences across participants, to ascertain the likelihood of an order effect. Despite our design of randomizing sequence, it was discovered that a skewed distribution occurred, where half of the sample (N=36) experienced reading as the last distraction conditions. This could have led to variables like fatigue affecting recognition performance. As such, to test for order effect, a 3x2 repeated measures ANOVA was conducted to analyse how the sequence number of distractions, regardless of distraction type, and test phase affected recognition sensitivity.

There was a trend of decreasing recognition sensitivity after a distraction for all sequence numbers, summarized in **Table 2**. The ANOVA showed that a main effect of test phase on d' was present ($F_{(1,35)} = 157.453, p < .001, \eta_p^2 = .818$). Post-hoc paired samples T-tests concluded that sensitivity became significantly lower in the delayed test phase compared to immediate test phase for first ($t_{(35)} = 7.594, p < .001$), second ($t_{(35)} = 5.890, p < .001$), and third ($t_{(35)} = 9.896, p < .001$) sequence numbers respectively (See **Figure 4.**). This means the negative effects of distractions were consistent across sequence numbers. However, no main effects of sequence number on recognition sensitivity were found (sphericity assumption violated; Mauchly's test $p = .025$, Greenhouse-Geisser corrections applied) ($F_{(1.674,58.593)} = 1.331, p > .05, \eta_p^2 = .037$). Average d' did not significantly differ across the first ($1.21 \pm .50$), the second ($1.40 \pm .86$) nor the third ($1.24 \pm .84$) sequence number (See **Figure 4.**). Finally, no significant interaction was found between test phase and sequence number ($F_{(2,70)} = 2.122, p > .05, \eta_p^2 = .057$). Therefore, since no main effects of sequence number on recognition sensitivity were found, and no interaction between sequence and test phase was present, it strongly indicated that order effect was not prominent in our study.

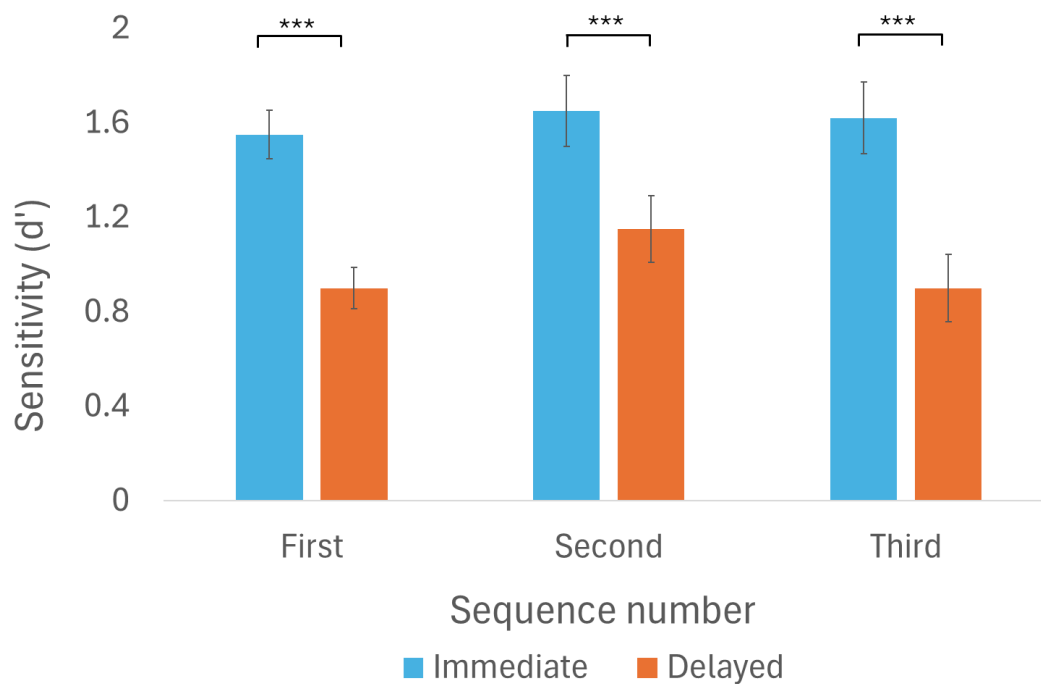
Table 2.

Means and standard deviation for recognition sensitivity (d') between immediate and delayed recognition phases across sequence numbers.

Sequence number	Immediate recognition		Delayed recognition	
	d'		d'	
	M	SD	M	SD
First	1.55	.62	.90	.52
Second	1.65	.90	1.15	.85
Third	1.62	.91	.90	.86

Figure 4.

*Average recognition sensitivity for immediate and delayed test phases across different distraction sequence numbers. Error bars represent standard errors from the mean. *** $p < .001$, ** $p < .01$, * $p < .05$.*



3.4. Response bias

Although response bias does not relate to our hypotheses, it presents a potential confounding variable to recognition sensitivity (Rottello & Macmillan (2007) and thus was analysed too. Results showed that response bias tends to become negative in the delayed test phase, meaning participants would become more liberal with classifying words as ‘old’ after distractions (See **Table 3.**). A 3x2 repeated measures ANOVA revealed significant main effects of test phase on c ($F_{(1,35)} = 10.463, p = .003, \eta_p^2 = .230$). Post-hoc paired samples t-tests revealed that c significantly decreased in the delayed phase compared to immediate phase for reading condition ($t_{(35)} = 5.155, p < .001$), but not for TikTok ($t_{(35)} = 1.919, p > .05$) and YouTube ($t_{(35)} = 1.146, p > .05$) conditions respectively (See **Figure 5.**). However, no main effects were found for distraction type on c , ($F_{(2,70)} = .451, p > .05, \eta_p^2 = .013$), and no significant interaction was found between phase and distraction type ($F_{(2,70)} = 2.468, p > .05, \eta_p^2 = .066$). These results suggested that response bias only significantly changes after a reading distraction, but overall bias is not impacted differently depending on distraction types.

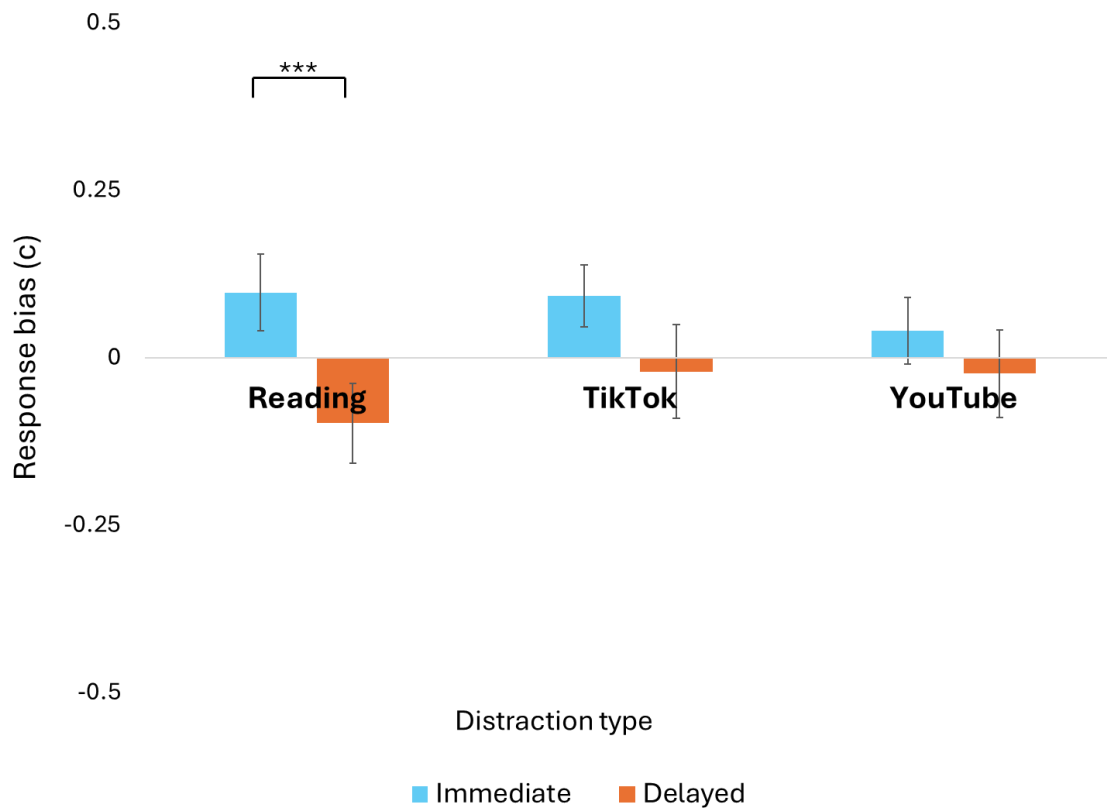
Table 3.

Means and standard deviation for response bias (c) between immediate and delayed recognition phases across distraction conditions.

Distraction	Immediate recognition		Delayed recognition	
	c		c	
	M	SD	M	SD
Reading	.097	.342	-.098	.358
TikTok	.092	.280	-.021	.419
YouTube	.040	.297	-.024	.394

Figure 5.

*Average response bias (c) for immediate and delayed test phases across different distraction conditions. Error bars represent standard errors from the mean. *** $p < .001$, ** $p < .01$, * $p < .05$.*



4. Discussion

4.1. *Task-switching's impact on recognition*

Recognition sensitivity and confidence ratings were both found to be degraded in the delayed relative to the immediate test phase. This is consistent with the wealth of literature surrounding cognitive interference, individuals task-switching to a distraction faced impaired recognition due to a 'switch cost' in working memory (Liefoghe et al, 2008; Muhmenthaler & Meier, 2019). Understandably, an argument could be made that degraded performance may be affected by natural memory decay after a temporal delay. However, various studies have shown that the effects of temporal memory decay are usually insignificant in an experimental context (Berman et al, 2009; Lewandowsky et al, 2009). For example, Oberauer and Lewandowsky (2013) conducted an analysis of individuals' verbal working memory retention across a range of temporal delay conditions, each with a 100% increase in interval between encoding and retrieval. They discovered that delay duration has no significant influence on memory retention, *i.e.* individuals do not forget more encoded items simply due to waiting longer until retrieval. Therefore, we conclude that the degraded performance found in delayed test phase for both sensitivity and confidence rating is a product of task-switching interferences, rather than memory decay.

Surprisingly, response bias was found to decrease after a reading condition, but not for TikTok nor YouTube conditions. Kantner and Lindsay (2012) proposed that response bias is a fixed cognitive trait rather than a variable of performance. Their experiments showed that response bias tends not to change through repeated ONR tests, upwards to one-week apart. So, the fact that we detected a change in participants' response biases may challenge this position. Notably, Kantner and Lindsay's study did not implement task-switching paradigms into their ONR tests. Thus, it can be inferred that response bias is susceptible to change only when task-switching is experienced. Furthermore, Rottello and Macmillan (2007) state that although response bias is a strong confounding variable for recognition sensitivity, studies usually focused solely on sensitivity to draw inferences about recognition performance. As such, it may be more accurate to conclude that for reading, specifically, the degraded recognition sensitivity found after distraction is underlined by changes in response bias, instead of direct effects on recognition sensitivity. However, since few studies are centred around task-switching's effects on ONR response

biases, it leaves much room for interpretation and future research on why reading specifically produces such results.

4.2. *Confidence ratings*

A discrepancy was found between recognition confidence and sensitivity, where distraction type was found to significantly affect recognition sensitivity, but not confidence ratings. This is not entirely surprising, as evidence has suggested that memory confidence and accuracy are only weakly related (Bothwell et al, 1987), since memory confidence is a wholly subjective evaluations that is processed post-retrieval of information, while accuracy is an objective assessment of memory retrieval abilities (Chua et al, 2012). Additionally, Chua et al (2006) conducted an fMRI analysis of participants while engaged in a recognition test. Brain activation was measured during participants' response to the test itself, and when reporting recognition confidence levels. Their findings revealed that assessments of confidence can be isolated to unique neural regions compared to actual memory retrieval, like the medial temporal lobe. Thus, it is possible that while different distraction types can affect normal retrieval processes to varying degrees, they simply do not differentially impact the unique mechanisms behind memory confidence.

4.3. *Differences between distraction type*

Contrary to our predictions, TikTok was not discovered to impact recognition sensitivity more negatively than other distractions. This contradicts Chiossi et al's (2023) findings, where TikTok's influence over PM was found to be more severe compared to YouTube, Twitter *etc.* Obviously, the key difference is that our study focused on RM components like episodic memory instead of PM. However, the literature has shown that increased cognitive loads are consistently linked to impairments in episodic memory (Camos and Portrat, 2014), as well as PM performances (Meier & Zimmermann, 2015). Thus, assuming the previous theories on SFVs' cognitive overloading capacity hold true, why may TikTok's detrimental effects be restricted to PM, and not RM? There are two explanations to consider.

First, although CLT has been applied to both memory domains, neurological evidence proposes that PM and RM are underlined by distinct neural processes (Palmer &

McDonald, 2000). West and Krompinger (2005) state that the retrieval process between PM and RM are initiated by different factors: in RM, retrieval is prompted by explicit stimuli (faces, words *etc*), whereas in PM, retrieval is prompted by a detection of cues (remembering to do 'x' when 'y'). To test this, they conducted an imaging study of participants' event-related potential (ERP) while doing RM and PM tasks that were matched as closely as possible. Their analysis revealed that while there is overlapping ERP during retrieval stages across RM and PM tasks, unique processing does exist during PM tasks, such as the N300 over several occipital regions, components strongly linked to cue detection and coordination. Taken together, this offers one explanation for our contrasting findings with Chiossi et al (2023). It could be that TikTok's cognitive loading capacity as a distraction only impairs the cue detection and coordination processes unique to PM, while leaving RM processes mostly unaffected.

Second, TikTok use only disrupt memory encoding, and not consolidation processes. As previously mentioned, SFVs cognitive loading capacity can be attributed to disruptions in event segmentation processes (Paltaratska, 2023; Li et al, 2024). However, event segmentation is mainly a memory encoding processes, where information is automatically segmented before being stored as memories (Zacks & Swallow, 2007). Thus, for our study, TikTok use would be less influential in impairing episodic memory, since distractions were administered after an encoding stage. In fact, according to Bilkey and Jensen (2019), 'event boundary markers', meaning clear signs that an 'event' is ending, are significantly linked to activation of the hippocampal regions associated with memory consolidation. Given that TikTok contains rapid context switches that increase the presence of event boundary markers (Paltaratska, 2023), it may be implied that consolidation would be enhanced rather than degraded during TikTok use. This was slightly reflected in our results, although no difference in recognition impacts was found, the TikTok condition did display the best recognition performance in the delayed test phase.

Incidentally, one of the few unexpected results was that the reading condition exhibited a worse recognition sensitivity compared to TikTok condition in the delayed test phase. Some evidence does suggest that reading may incur a higher cognitive load than assumed, especially when individuals are bored by reading. Studies have shown that when individuals are bored, behaviours like mind-wandering takes place, where attention is allocated to unrelated tasks or information (Blondé et al, 2022). This, in turn, takes away

resources from primary tasks and degrades cognitive abilities like recognition (Lapteva et al, 2025). Mind-wandering has been heavily applied to the context of reading. Feng et al's (2013) study proposed that texts that are difficult to read tends to provoke more mind-wandering in participants compared to texts that are easy to read, leading to lower comprehension for difficult texts. As such, our choice of using academic articles may have added a layer of difficulty to reading distractions, provoking boredom and mind-wandering in participants, ultimately increasing CL and hindering recognition.

4.4. *Potential order effect*

The most puzzling finding was that a significant difference in recognition sensitivity between distraction types was already present in the immediate recognition phase. Given that no order effect was discovered during analysis, the difference could not be attributed to the sequence of distractions, despite our skewed frequency distribution. This leaves only a few logical conclusions for such a result. A simple explanation would be that unforeseen confounds were left unaccounted for, for instance, procedural differences that either disrupted or enhanced immediate recognition for participants during specific distraction conditions. Alternatively, it could be that an order effect did exist but was not detected by our analysis method. We utilized a direct approach of comparing d' between every sequence number, while a more extensive method is to compare the d' between every distraction condition at every possible sequence (TikTok first, vs YouTube first vs Reading first *etc*). However, this process would then expose us to a higher likelihood of type I error, due to the larger number of statistical tests needed. Although, if we entertain the idea that an order effect was discovered using such methods, more plausible explanations could then be provided for the difference found in the immediate test phase. For example, theories drawing from predictive task-switching state that switch costs can be altered based on individual's predictions of task-switching (Barton et al, 2006; Duthoo et al, 2012). Predictive task-switching would be highly relevant to our experiment, since our design entails participants being aware of what the last distraction in their sequence is.

4.5. *Limitations and future directions*

A key limitation of our study was the level of control applied to distractions. Our design offered participants the choice to select YouTube videos and readings. The different

choices could have varied in properties of pace and arousal for YouTube videos (Lang et al, 1999), and difficulty of text for readings (Feng et al, 2013). This presents a possible confound of having different cognitive loading capacities within each distraction type, which may skew recognition performance results. Although, given that Chiossi et al (2023) discovered significant findings while also offering choices of YouTube videos, it could be argued that the difference between media types is large enough to disregard variations within media type. Moreover, we created only a single temporary TikTok account to be used jointly by participants. According to Zhao (2021), the longer and more frequent a TikTok app is used, the more accurate the algorithm will be in filtering videos for the user. Therefore, there was no guarantee that TikTok feeds are truly random for each participant, since the recommendation system could have been altered over the course of the experiment based on video genre and duration. A way to address for this issue was observed in a previously mentioned study by Su et al (2021). Su and colleague pre-selected a list videos on a newly downloaded TikTok app, recording and storing them for use during testing. Therefore, each participant was given an identical list of random TikTok videos to be watched in the ‘random feed’ condition.

Aside from addressing the limitations, future studies should employ direct measurements of CL during distraction to ascertain the true difference in cognitive loading capacity between SFVs, long video formats, and reading. Eye-tracking methods have already been employed reliably to detect changes in event segmentation processing load during TikTok use (Paltaratska, 2023; Mahmoudi et al, 2024). However, they have yet to be applied to task-switching contexts. Additionally, it may also be worth investigating whether personalized TikTok videos would produce distinct results from our study, given the mixed evidence currently in the literature, where personalized videos are simultaneously documented to be more arousing while less influential on event segmentation (Su et al, 202; Li et al, 2024).

4.6. *Conclusion*

As far as we know, this is the first study to investigate how different media types affect episodic memory processes under a task-switching paradigm. We concluded that watching TikTok videos did not significantly impact recognition memory more than watching a continuous video or reading. This study contributes to various established theories in

cognitive psychology, like cognitive overload, event-segmentation, and task-switching. In the wider scheme, it also informs the users of TikTok and YouTube on the cognitive influences of the platforms they use, improving consumer awareness.

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Appendix

Appendix A.

Ethics approval code: PS18217



School of Psychology & Neuroscience Ethics Committee

26 November 2024

Dear Xiu Yang

Thank you for submitting your ethical application which was considered at the School Ethics Committee meeting on 14th November 2024.

The School of Psychology & Neuroscience Ethics Committee, acting on behalf of the University Teaching and Research Ethics Committee (UTREC), has approved this application:

Approval Code:	PS18217	Approved on:	26/11/2024	Approval Expiry:	26/11/2029
Project Title:	Tiktok and context switching: the effects of short-form videos on recognition memory				
Researcher:	Xiu Yang Kooi				
Supervisor:	Dr Akira O'Connor				

The following supporting documents are also acknowledged and approved:

1. Research Protocol
2. Advertisement
3. Participant Information Sheet
4. Participant Consent Form
5. Participant Debriefing Form

Approval is awarded for 5 years, see the approval expiry date above.

If your project has not commenced within 2 years of approval, you must submit a new and updated ethical application to your School Ethics Committee.

If you are unable to complete your research by the approval expiry date you must request an extension to the approval period. You can write to your School Ethics Committee who may grant a discretionary extension of up to 6 months. For longer extensions you must submit an ethical review application form.

If you need to make changes to your project, you must submit an ethical amendment application.

You must report any serious adverse events, or significant changes not covered by this approval, related to this study immediately to the School Ethics Committee.

Approval is given on the following conditions:

- that you conduct your research in line with:
 - the details provided in your ethical application

Cont.

School of Psychology & Neuroscience Ethics Committee
School of Psychology & Neuroscience, St Mary's Quad, South Street, St Andrews, Fife, KY16 9JP
Telephone: 01334 462071 Email: psyethics@st-andrews.ac.uk
The University of St Andrews is a charity registered in Scotland: No SC013532

- the University's [Principles of Good Research Conduct](#)
 - the conditions of any funding associated with your work
- that you obtain all applicable additional documents (see the ['additional documents' webpage](#) for guidance) before research commences.

You should retain this approval letter with your study paperwork.

Yours sincerely,



Dr David Tait
Convenor of the School Ethics Committee

cc. Dr Akira O'Connor

School of Psychology & Neuroscience Ethics Committee
School of Psychology & Neuroscience, St Mary's Quad, South Street, St Andrews, Fife, KY16 9JP
Telephone: 01334 462071 Email: psyethics@st-andrews.ac.uk
The University of St Andrews is a charity registered in Scotland: No SC013532

Appendix B.

TikTok addiction questionnaire

(0 = Not Applicable 1 = Rarely 2 = Occasionally 3 = Frequently 4 = Often 5 = Always)

1. How often do you find that you stay on TikTok longer than you intended? ____
2. How often do you neglect household chores to spend more time on TikTok? ____
3. How often do you prefer the excitement of TikTok to intimacy with your partner? ____
4. How often do you form new relationships with fellow TikTok users? ____
5. How often do others in your life complain to you about the amount of time you spend on TikTok?

6. How often do your grades or schoolwork suffer because of the amount of time you spend on TikTok? ____
7. How often do you use TikTok before something else that you need to do? ____
8. How often does your job performance or productivity suffer because of TikTok? ____
9. How often do you become defensive or secretive when anyone asks you what you do on TikTok? ____
10. How often do you block out disturbing thoughts about your life with soothing thoughts of TikTok? ____
11. How often do you find yourself anticipating when you will go on TikTok again? ____
12. How often do you fear that life without TikTok would be boring, empty, and joyless? ____
13. How often do you snap, yell, or act annoyed if someone bothers you while you are on TikTok?

14. How often do you lose sleep due to being on TikTok? ____
15. How often do you feel preoccupied with TikTok when off-line, or fantasize about being on TikTok? ____
16. How often do you find yourself saying "just a few more minutes" when on TikTok? ____
17. How often do you try to cut down the amount of time you spend on TikTok and fail? ____
18. How often do you try to hide how long you've been on TikTok? ____
19. How often do you choose to spend more time on TikTok over going out with others? ____
20. How often do you feel depressed, moody, or nervous when you are not using TikTok, which goes away once you are back on TikTok? ____

Appendix C.

List of YouTube videos used

The Coolest ""Country"" Flag You Need To Know (CGP Grey):

<https://youtu.be/U0wTDK0VOeY?si=pWRsNgNlnAeS8HZC>

You Are Two (CGP Grey):

<https://youtu.be/wfYbgdo8e-8?si=NJpfK1BawgrCysMe>

It's way different than you think (AsapSCIENCE):

<https://youtu.be/5sxxqxqVSN0?si=6W75ONW0Kf90EmIb>

The Great Depression – 5 Minute History Lesson (The Plain Bagel)

<https://youtu.be/62DxELjuRec?si=B0DyUANg9ZsXpKJt>

You Can't Touch Anything (Vsauce)

<https://youtu.be/yE8rkG9Dw4s?si=vmCp3Tci6dCKNztP>

Appendix D.

List of articles used

- Daniele, M., Fasoli, F., Antonio, R., Sulpizio, S., & Maass, A. (2020). Gay voice: Stable marker of sexual orientation or flexible communication device?. *Archives of Sexual Behavior*, 49, 2585-2600. <https://doi.org/10.1007/s10508-020-01771-2>
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