Original Papers

Polish Psychological Bulletin
2024, vol. 55 104–117
DOI: 10.24425/ppb.2024.150361

Kamil Szymański[1]

[1] *SWPS University of Social Sciences and Humanities, Wroclaw, Poland*

CORRESPONDING AUTHOR – Kamil Szymański, kszymanski@swps.edu.pl

Relationship of affect, memory and number intuition with human time perception

Abstract: Time perception is a fundamental process for all animals. We are all familiar with discrepancies in how duration is perceived. This paper explores the following questions: How does the brain perceive time, and what are the sources of these discrepancies? We conducted four studies to examine the effects of affect and arousal on subjective time perception. Employing the Scalar Expectancy Theory model, our final study investigated the role of working memory overload. Additionally, we explored the potential influence of information theory features associated with the stimuli across all studies. Using Bayesian data analysis, we demonstrated that the widely recognized effects of valence, arousal, and their interaction induced by visual stimuli might be artifacts. Notably, a significant effect of valence was observed only in one study, associated with working memory overload. We also highlighted the potential roles of luminance and entropy of visual stimuli, but only in direct duration estimations. The sole persistent effect was related to the objective duration of stimulus exposure. All studies utilized affective visual stimuli. Our findings underscore the necessity for further investigation into human time perception on a millisecond to second scale, particularly concerning stimulus-related factors. Additionally, our results emphasize the importance of methodological considerations in studying human time perception.

Keywords: *time perception, information theory, entropy, affect, working memory*

INTRODUCTION

Time is a fundamental phenomenon in our world. Many of us can recall watching an exciting movie or attending an engrossing lecture where time seemed to pass in half its actual duration. Conversely, a tedious lecture might feel interminable. This divergence between objective and subjective time has been a subject of scientific inquiry for decades (Danckert & Allman, 2005; Gilliand, Hofeld, & Eckstrand, 1946; Woodrow, 1951; Grondin, 2010). Initially, researchers used the metaphor of an “internal clock” to describe our time perception mechanisms. However, as understanding deepened, more complex questions emerged regarding the nature of subjective time, such as the factors responsible for perceptual differences across species, and the implications of time perception in psychological dysfunctions (Pöppel, 1978; Eagleman, 2008; Droit-Volet & Meck, 2007; Tramacere & Allen, 2022; Thönes & Oberfeld, 2015; Berlin & Rolss, 2004).

What insights does cognitive science offer about our perception of time? John Gibbon’s research on macaques introduced the most established cognitive model, the Scalar Expectancy Theory (*SET*), which has since been elaborated upon (Gibbon, 1977; Gibbon et al., 1984; Allan & Gibbon, 1991; Block & Zakay, 1996; Droit-Volet & Wearden, 2001). The visualization of this model, depicted in Figure 1, describes the first stage of time processing. In this model, a *Pacemaker* generates cyclic impulses that are transmitted to an *Accumulator* via an *Attention Gate*, which regulates the flow of information. *The Accumulator* counts these impulses. Initially, *the Attention Gate* might seem like a bottleneck in the system, but is it the sole factor influencing performance? This model suggests an underlying counting process integral to the mechanism.

Funding source with grant number – Diamentowy Grant (nr projektu DI2017010547)

Subsequent efforts led to the establishment of the Approximate Number System (*ANS*), detailed by Van de Rijt et al. (2003) and Dehaene (2011). The primary objective of this system was to delineate the essential processes underlying numerical operations. Brannon and Merritt (2011) provided evidence for this system's fundamentality, demonstrating a shared numerical capacity between humans and non-human animals. Further studies by Agrillo, Piffer, and Adriano (2013), as well as Gilmore, McCarthy, and Spelke (2010), suggested that the ANS correlates with symbolic mathematical skills, minimally influenced by educational background. However, scientific consensus on these findings remains elusive (Park & Brannon, 2013; Piazza et al., 2013; Guillaume & Gavers, 2016). Measuring the *ANS* presents challenges, as indicated by Dietrich, Huber, and Nuerk (2015) and Smets, Gebuis, and Reynvoet (2013).

The methods for assessing *Number Sense* vary. For instance, non-symbolic assessments involve tasks where participants compare the magnitudes of two sets, such as dots (Halberda, Mazzocco, & Feigenson, 2008). Alternatively, symbolic assessments require participants to choose between two numerical values displayed on-screen, determining which is greater or lesser (Sasanguie et al., 2012). Comparative studies by Gilmore, Attridge, and Inglis (2011) and findings by DeWind et al. (2015) suggest that numerosity is perceived as a visual quantity and that numbers are understood in terms of magnitude.

Further, a meta-analysis by Schneider et al. (2015), involving 45 articles with over 17,000 participants, demonstrated that magnitude processing is correlated with mathematical competencies. Another meta-analysis, reviewing 19 studies, indicated that the relationship between non-symbolic numerical magnitude and mathematics achievement weakens after age six (Fazio et al., 2014).

Moreover, because of its low-level nature, it brings another issue. Hyde, with collaborators, showed that the development of numerical representation occurred before linguistics (Hyde et al., 2010) which can be treated as an argument in favor of how fundamental our *Number Sense* is. Meck and Church compared numerical and time representation of rats (Meck & Church, 1983) and showed no visible differences between those structures. Moreover, after the application of methamphetamine, the performance of both mechanisms increased. It is stated that the time perception in the milliseconds-seconds range responsible is the cortical region and specified *Basali Ganglia* (Meck, Penney, Pouthas, 2008). Authors additionally postulate that *Dorsal Striatum* may be a core timer based on its role in estimation and reproduction tasks. Most studies connecting temporal processing with the numerical system are made on animals. Leon and Shadlen (2003) showed activation of *the Posterior Parietal Cortex* when macaques estimated exposition time of two circles. There are also indicators that this region has neurons responsible for numerical processing (Walsh, 2003; Javadi et al., 2014).

Furthermore, the fundamental nature of *Number Sense* is highlighted by its development prior to linguistic

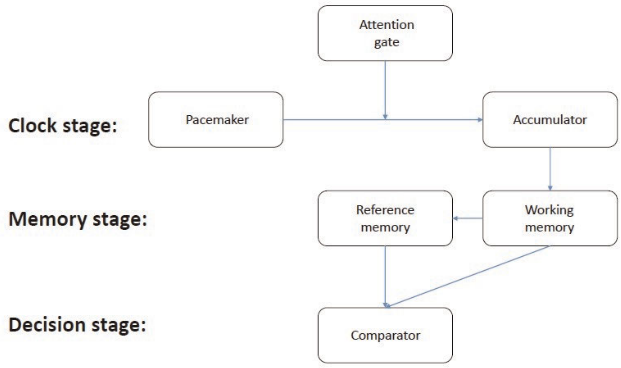

Fig 1. Visualization of the Scalar Expectancy Theory

abilities, as demonstrated by Hyde and colleagues, who found that numerical representation develops before linguistic skills (Hyde et al., 2010). This suggests the primacy of numerical cognition. Meck and Church (1983) explored the representation of numbers and time in rats, finding no significant differences between these cognitive structures. Interestingly, their performance in tasks improved following the administration of methamphetamine. This points to a link between neurochemical processes and cognitive performance.

Research by Meck, Penney, and Pouthas (2008) identifies the cortical areas and the *Basal Ganglia* as critical for time perception in the milliseconds to seconds range. They further hypothesize that the *Dorsal Striatum* plays a central role in timing, based on its involvement in estimation and reproduction tasks. Although most studies examining the connection between temporal and numerical processing have been conducted on animals, they offer valuable insights. For instance, Leon and Shadlen (2003) observed activation in the *Posterior Parietal Cortex* of macaques during tasks estimating the exposure time of two circles, suggesting this area's involvement in both temporal and numerical processing. This is supported by findings that neurons within this region are implicated in numerical tasks (Walsh, 2003; Javadi et al., 2014).

Numerous investigations have utilized the Scalar Expectancy Theory (*SET*) model to explore the influence of affective factors on time perception. Angrilli et al. (1997) demonstrated this by showing participants affective images from *the International Affective Picture System* (*IAPS*; Lang, Bradley, & Cuthbert, 2008), for durations of 2, 4, or 6 seconds, while also collecting psychophysiological measurements. Participants rated durations either on an analogue scale or by reproducing the stimulus duration. Findings indicated that duration reproduction was typically associated with greater underestimation compared to analogue evaluation. For stimuli with low arousal, negative images were perceived as shorter than positive ones; conversely, under high arousal conditions, this relationship reversed.

This pattern was similarly observed with auditory stimuli by Noulhiane et al. (2007), where negative, high-arousal sounds were estimated to last longer than positive sounds. Additionally, high-arousal sounds were generally perceived as longer than low-arousal ones.

The impact of affect on time perception extends to facial expressions as well. Droit-Volet and colleagues (2004; Droit-Volet & Meck, 2007) found that exposure to human faces expressing various emotions (happiness, anger, fear, disgust, and sadness) led participants to overestimate the duration of exposure to angry and fearful faces. These findings were consistent across different exposure times ranging from 400 to 1600 milliseconds and were even observed in children (Gil, Niedenthal, & Droit-Volet, 2007).

Subsequent research by Fayolle, Gil, and Droit-Volet (2015), and Droit-Volet and Berthon (2017), corroborated these observations, suggesting that high arousal scenarios accelerate the internal clock's pacing. This emotion-based modulation of time perception was also demonstrated using indirect stimuli by Yamada and Kawabe (2011), who showed that negative affect could unconsciously increase the pace of the internal clock.

Further, Thönes and colleagues (2018) found that participants consistently overestimated the duration of blue stimuli compared to red ones, pointing to the influence of fundamental stimulus properties on time perception. Recent meta-analyses by Cui et al. (2022) affirmed these effects, highlighting that negative stimuli are generally overestimated relative to positive ones, and that higher arousal correlates with greater temporal dilation. Moreover, they noted that the discrimination and estimation paradigms often yield larger discrepancies than reproduction paradigms, reinforcing the value of the estimation paradigm in research.

The second component of the Scalar Expectancy Theory (*SET*) model involves memory. Pan and Luo (2012) proposed that perceived duration might be modulated by working memory. This concept has also been explored neuroscientifically; for example, Üstün and colleagues (2017) found a correlation between working memory, time perception, and *peristriate cortical* activity. Additionally, Lee and Yang (2019) observed that children with *Attention Deficit Hyperactivity Disorder* (*ADHD*) exhibited poorer time discrimination abilities than their peers, though differences became non-significant when controlling for working memory and intelligence.

Similarly, Roy et al. (2012) demonstrated a potential link between time perception impairments and memory deficits in individuals with schizophrenia. The relationship between numerical cognition and working memory has also been investigated, particularly in educational contexts. Kroesbergen and Van Dijk (2015) noted that children with lower scores in Number Sense or visual-spatial working memory performed worse on mathematics tests. This finding was supported by Toll, Kroesbergen, and Van Luit (2016), who identified visual working memory and Number Sense as predictors of math achievement among 670 children. However, van Bueren et al. (2022) suggested that these relationships are complex and necessitate further exploration.

Advancements in numerical analysis and growth of computational power have opened new avenues for data analysis, including the use of deep learning for analyzing visual stimuli (Bajammal et al., 2020). Modern computational techniques can extract extensive information from high-quality stimuli, with information theory playing a crucial role in understanding signals like pictures or sounds. Early work by Thomas and Weaver (1975) proposed that temporal judgments could be the result of both information processing and an internal timer. Recent research by Bilgli and colleagues (2020) found that exposure to different lighting colors affected perceived time, highlighting an underexplored area of study.

In terms of the relationship between information theory and memory, additional studies have provided insights. Qian et al. (2018) showed that saturation and brightness might influence the impact of depth on visual working memory. Moreover, Krahn (2018) suggested that memory could be affected by the color of the stimulus, indicating potential areas for future research.

Based on the studies described above, the following research questions were formulated:

1. Is there a relationship between human time perception and the affective nature of a stimulus as well as the arousal it is expected to induce?
2. Do models of human time perception require extension to include additional individual traits such as memory or *Approximate Number System*?
3. Are there physical characteristics of stimuli that play a key role in how people estimate time?

The study hypothesizes that affective traits and related arousal will act as predictors of time perception distortions, though these effects are anticipated to be weaker than those reported in the existing literature. Furthermore, it is assumed that physical characteristics of stimuli such as entropy, luminance, and complexity will take a principal role in the model. Working memory overload is also considered a significant predictor as well as individual *ANS* efficiency. To address the proposed research questions and hypotheses, four experimental procedures were conducted. This approach was necessitated by the inherent complexity of defining human time perception, which has led to the development of various research methodologies. Given the impossibility of verifying the full spectrum of methodologies, the procedures described below were selected to align with the mainstream research on the relationship between time perception and the affective components and arousal of visual stimuli presented in millisecond to second intervals.

EXPERIMENT 1

Participants

In the first experiment, 80 students from the University of Social Sciences and Humanities participated, including 58 females. The average age of the participants was 21.55 years (*SD* = 3.64). Participants received compensation for their involvement. All had normal or corrected-to-normal vision. Ethical approval for the study was obtained from the Ethics Board at the University of Social Sciences and Humanities.

Design and Procedure

The goal of the first experiment was to examine the known effects of the affective features of a stimulus and induced valence, as well as its physical characteristics, on participants' time perception distortion. To achieve this goal, a classical procedure was employed where participants directly evaluated the duration of a visual stimulus using a slider.

The experimental stimuli were displayed on a 23-inch monitor with a refresh rate of 60 Hz in the university laboratory. Participants were seated approximately 50 cm from the screen. The initial phase of the experiment employed the *Panamath* software (Halberda, Mazzocco, & Feigenson, 2008) to assess numerical cognition. In this task, participants were required to identify the larger set of dots, which alternated in color between yellow and blue. The mean score from this task was used as an indicator of the participants' *Number Sense*.

The subsequent phase focused on time perception and was conducted using the Python programming language with the PsychoPy library (Pierce, 2007). Initially, participants were shown a sample duration followed by a fixation point ("+") and then a black box displayed for 400 ms, followed by the same box displayed for 1600 ms. Information regarding the duration of visibility was provided prior to the appearance of the black boxes. A training phase ensued, where random neutral pictures were displayed for durations ranging from 400 ms to 1600 ms across 14 trials (two for each duration). Responses were collected via a mouse-operated slider.

The main phase of the experiment followed the training, wherein participants were exposed to highly affective images, either positive or negative, sourced from the IAPS database (Lang, Bradley, & Cuthbert, 1997). A complete list of the pictures used is included in the attachment. Visual representations of the procedural framework for this phase are provided in Figure 2. Throughout all experiments, information theory variables were extracted from the stimuli. We examined two of these variables:

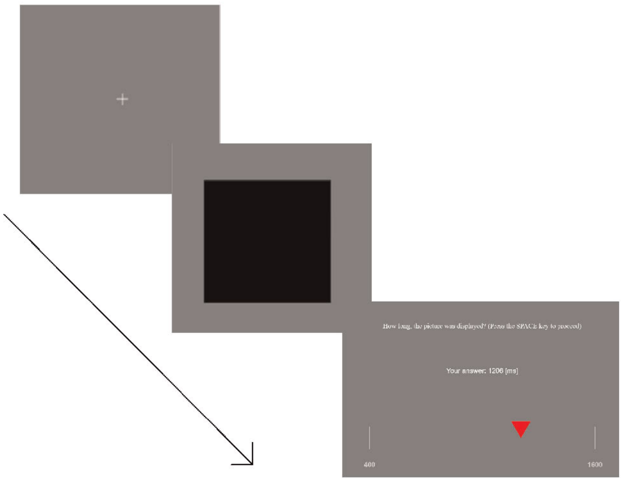

Fig 2. General framework for studies 1-3 (time estimation from experiment 1)

– Entropy – obtained from the histogram distribution of the 8-bit grey level intensity

$$H = -\sum p(x)\log(p(x))$$

– Luminance – average pixel values of the grayscaled image

Results

The statistical analyses were conducted using multilevel Bayesian models implemented through the brms package (Bürkner, 2017) in R (version 4.2.0) (R Core Team, 2022). All models were fitted using the *Markov Chain Monte Carlo* (*MCMC*) method with four chains, each consisting of 7,000 iterations, with the first 3,000 iterations discarded as burn-in. Predictors were standardized, and the dependent variable, estimation error (objective duration minus subjective duration), was defined. Model selection was based on the *expected log predictive density method* (Vehtari, Gelman, & Gabry, 2017).

The initial model, termed the null model, with additional random effects incorporating a free intercept for each participant was established. Subsequent analyses introduced *Number Sense* and the objective time as predictors, along with a random slope for objective time. This model indicated that *Number Sense* significantly predicted duration estimation error, with a mean effect size of M = -32.29 (95% CI [-49.76, -12.45]). Additionally, a negative relationship was observed between subjective and objective time, M = -141.86 (95% CI [-158.64, -125.42]).

The third model incorporated valence, arousal, and their interaction, alongside random effects for objective time, valence, and arousal. The results showed valence as a positive predictor of duration estimation error, M = 8.31 (95% CI [3.43, 13.24]), and both objective time, M = -141.02 (95% CI [-158.35, -123.93]), and *Number Sense*, M = -30.80 (95% CI [-49.49, -12.13]), were negative predictors. Contrary to previous studies, arousal did not significantly predict duration estimation error, M = -2.12 (95% CI [-6.21, 2.03]), nor did the interaction between valence and arousal, M = -2.65 (95% CI [-6.51, 1.15]).

In the final model, information theory variables were included. Based on *elpd* we see that it caused a slight improvement of the model, with the final R^2 = 0.50 (95% CI[0.49, 0.51]). The first level residual variance is M = 40505.59 (95% CI [39402.25, 41664.97]). The second level residual variance is M = 15065.11 (95% CI [11001.91, 20741.76]). Finally, it turned out that *Number Sense* (M = -31.06 (95% CI[-49.98, -12.20]), valence (M = 8.41 (95% CI[3.47, 13.37]), entropy (M = 10.47 (95% CI[4.78, 15.93]) and luminance (M = -8.14 (95% CI [-13.73, -2.41]) can be treated as predictors of duration estimation error. In the context of random slopes, we found that objective time characterize of high variance M = 5783.60 (95% CI [4173.16, 8020.99]). Smaller variance was found in the case of valence M = 146.41 (95% CI [4.71, 377.14]) and arousal 24.21 (95% CI [0.03, 173.45]).

Table 1. Summary of models from experiment 1

	Model 1	Model 2	Model 3	Model 4
Predictors	*Est.* *[95% CI]*	*Est.* *[95% CI]*	*Est.* *[95% CI]*	*Est.* *[95% CI]*
Intercept	-122.71 [-149.82, -95.64]	-122.31 [-148.45, -95.77]	-120.94 [-148.55, -93.86]	-122.17 [-148.92, -95.70]
Number Sense		-31.29 [-49.76, -12.45]	-30.80 [-49.49, -12.13]	-31.06 [-49.98, -12.20]
Objective time		-141.86 [-158.64, -125.42]	-141.02 [-158.35, -123.93]	-141.40 [-158.11, -124.40]
Valance			8.31 [3.43, 13.24]	8.41 [3.47, 13.37]
Arousal			-2.12 [-6.21, 2.03]	-0.98 [-5.14, 3.20]
Valence*Arousal			-2.65 [-6.51, 1.15]	-2.57 [-6.43, 1.29]
Entropy				10.37 [4.78, 15.93]
Luminance				-8.14 [-13.73, -2.41]
ΔELPD [standard error]	-2484.9 [58.4]	-14.4 [7.0]	-5.4 [3.7]	0.00 [0.0]
R^2	0.17	0.496	0.499	0.50

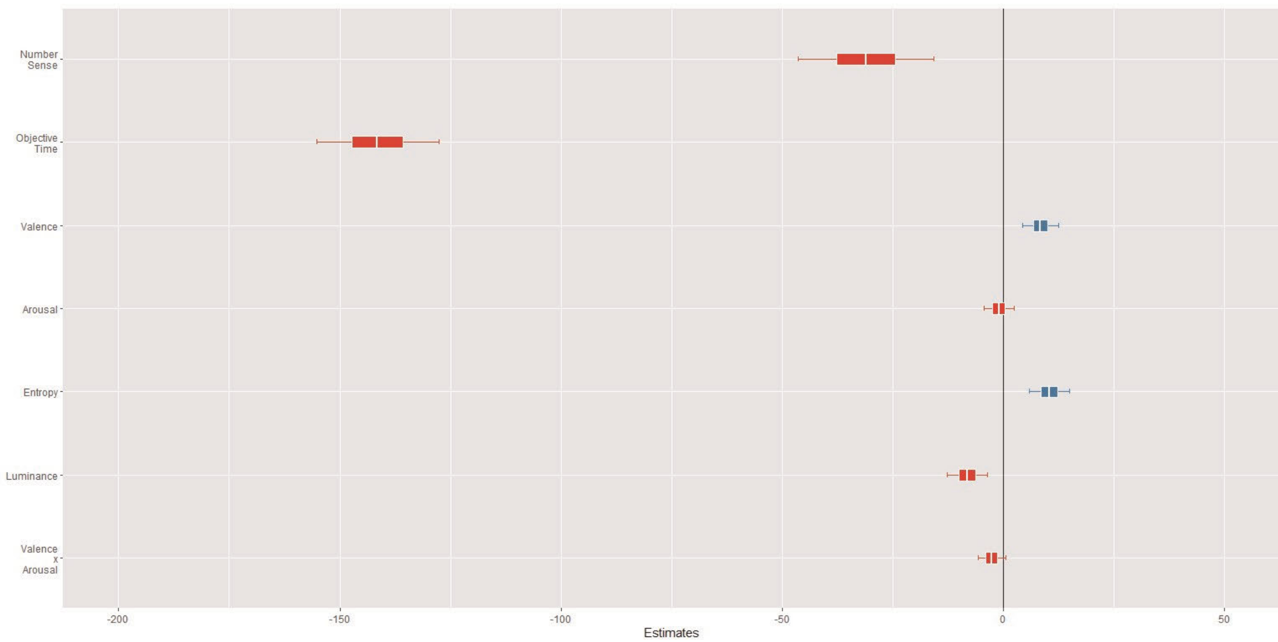

Fig 3. Posteriors of the final model for experiment no. 1

EXPERIMENT 2

Participants

Fifty-five students of the University of Social Sciences and Humanities participated in the second experiment (34 female). Mean age of participants was 24.20 (*SD* = 4.82). All of them were paid for their participation. All participants had a normal or corrected-to-normal vision. Study approval was granted by the University of the Ethics Board at the University of Social Sciences and Humanities.

Design and procedure

In the second study, we aimed to examine the same effects as in the first study, but this time we changed the method of evaluating the stimulus duration. Unlike the previous study, participants now had to reproduce the duration of the stimulus exposure by pressing the SPACE bar. This modification was implemented to determine if the results were independent of the method used for evaluation.

Stimuli were presented on a monitor (23', 60 Hz) at the University lab. Participant's *Number Sense* measurement were conducted analogous to the first experiment.

The second part of the study, where time perception was examined, was made in Python using the PsychoPy library (Pierce, 2007). After an instruction, participants saw sample duration. After the fixation point "+" a black box was visible for 400 ms. Next, the same black box was visible for 1600 ms. Before black boxes showed up, there was an information about how long pictures will be visible. After that, a training phase was made. In this phase random neutral pictures were shown for 400, 600, 800, 1000, 1200, 1400 or 1600 ms. There were 14 training trials (twice for each duration). Participants answered by pressing the SPACE key. When the SPACE key were pressed, the cross "+" sign was visible. After training trials, the main phase of the second stage started. Participants were informed that pictures in this phase will be highly affective either positively or negatively. Affective stimulus was chosen from the *IAPS* database (Lang, Bradley, Cuthbert, 1997). A list of pictures used in this study is in attachment. Visualization of the second part is shown in the figure no. 2.

Results

Statistical analyses of multi-level Bayesian models using the brms package (Bürkner, 2017) in R (version 4.2.0) (R Core Team, 2022) were made. All models were fitted using the Markov-Chain Monte Carlo method with four chains. Each chain has 7000 iterations, with the first 3000 burned. Predictors were standardized, and an estimation error (objective duration – subjective duration) was established as a dependent variable. Model selection was made using *the expected log predictive density method* (Vehtari, Gelman, & Gabry, 2017).

The initial model, termed the null model, included a free intercept. Subsequently, a random intercept for each participant was added. In the second model, *Number Sense* and objective time were introduced as predictors, with a random slope for objective time. The first level residual variance is M = 123510.07 (95% CI [119411.71, 127713.32]). The second level residual variance is M = 65229.16 (95% CI [44829.59, 96565.56]). This model demonstrated that objective time was a significant negative predictor of subjective time, M = -163.52 (95% CI [-192.29, -134.48]). A random effect of the slope of objective time was M = 10726.74 (95% CI [7160.54, 16371.20]). In this case, model has the lowest *elpd* with R^2 = 0.44 (95% CI [0.43, 0.46]).

The third model included valence, arousal, and their interaction, alongside random effects for objective time, valence, and arousal. The results indicated that objective time remained a negative predictor of subjective time, M = -162.86 (95% CI [-191.24, -134.53]).

Table 2. Summary of models from experiment 2

	Model 1	***Model 2***	***Model 3***	***Model 4***
Predictors	*Est.* *[95% CI]*	*Est.* *[95% CI]*	*Est.* *[95% CI]*	*Est.* *[95% CI]*
Intercept	-222.58 [-288.70, -153.79]	-216.87 [-285.52, -148.34]	-215.62 [-284.56, -148.03]	-217.80 [-283.99, -151.83]
Number Sense		-21.56 [-64.62, 22.54]	-24.36 [-65.60, 17.26]	-24.97 [-68.27, 17.35]
Objective Time		-163.52 [-192.29, -134.48]	-162.86 [-191.24, -134.53]	-163.39 [-191.28, -135.43]
Valance			-7.83 [-16.54, 1.07]	-6.98 [-15.98, 2.03]
Arousal			-1.92 [-10.78, 6.82]	-1.37 [-10.22, 7.32]
Valence*Arousal			0.79 [-7.34, 8.85]	-1.17 [-12.96, 10.66]
Entropy				-3.27 [-15.28, 8.77]
Luminance				0.89 [-7.15, 8.82]
ΔELPD [standard error]	-914.8 [69.1]	0.0 [0.0]	-2.7 [2.7]	-4.2 [3.0]
R^2 [95% CI]	0.28 [0.26, 0.29]	0.44 [0.43, 0.46]	0.45 [0.43, 0.46]	0.45 [0.43, 0.46]

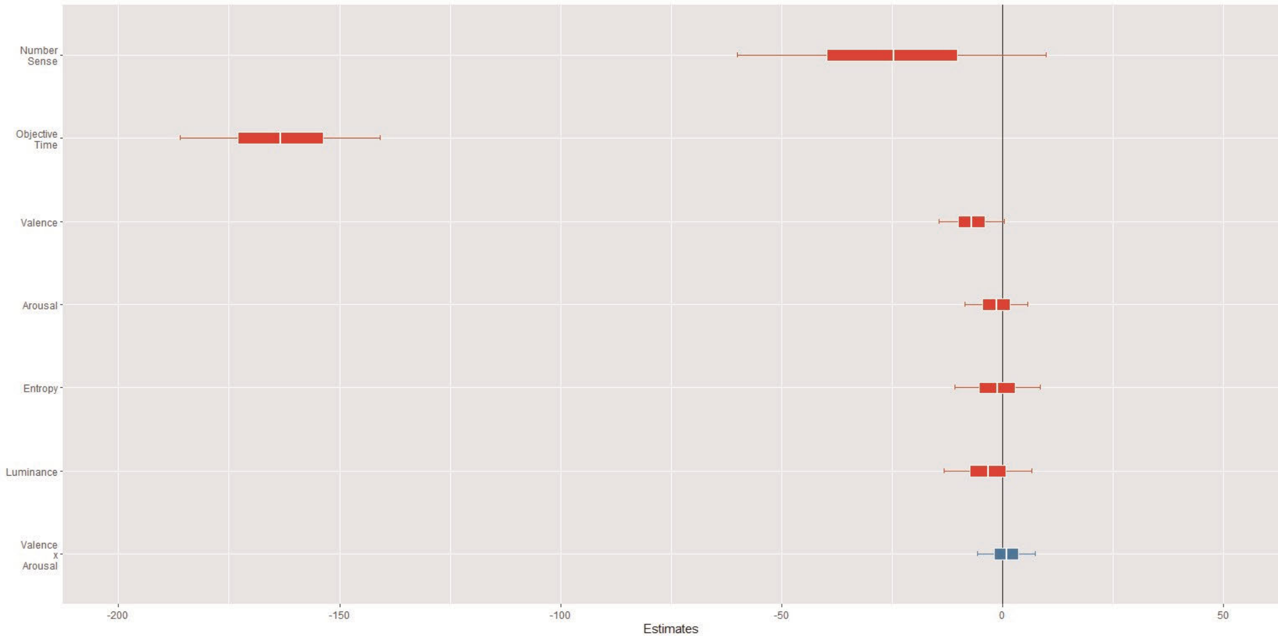

Fig 4. Posteriors of the final model for experiment no. 2

In the final model, information theory variables were incorporated. The analysis revealed that only objective time was a significant predictor of time discrepancy, M = -163.39 (95% CI [-191.28, -135.43]). The final model R^2 was 0.45 (95% CI [0.43, 0.46]).

EXPERIMENT 3

Participants

A total of 58 students of the University of Social Sciences and Humanities participated in the second experiment (38 female). Mean age of participants was 21.81 (SD = 4.55). All of them were paid for their participation. All participants had a normal or corrected-to-normal vision. Study approval was granted by the University of the Ethics Board at the University of Social Sciences and Humanities.

Design and procedure

In the third study, we replicated one of the most common methodologies in cognitive time perception research. Time perception distortion was assessed by classifying the duration of a previous event into one of two categories: where the subjective duration was closer to either the minimal or maximal end of the scale. The goal of this study was similar to the previous one: to determine if the known effects are independent of the experimental methodology.

The first part of the procedure, where we measured *Number Sense*, was analogous to the previous experiments. Differences arose in the second stage, where participants were shown samples of the shortest (400 ms) and longest (1600 ms) possible durations. Following this, a training phase was conducted. The task required participants to estimate the duration of a black box using two keyboard keys, representing the shortest and longest durations. Participants were asked to estimate whether the duration of the recent picture was closer to 400 ms or 1600 ms. The stimulus duration was randomly drawn from the set [400, 600, 800, 1000, 1200, 1400, 1600 ms]. After 14 training trials, the main phase of the second stage began. Affective stimuli were selected from the IAPS database (Lang, Bradley, & Cuthbert, 1997). A list of pictures used in this study is provided in the attachment. Instructions explaining the task were given before each part of the procedure.

Results

Statistical analyses of multi-level Bayesian models using the brms package (Bürkner, 2017) in R (version 4.2.0) (R Core Team, 2022) were made. All models were fitted using the Markov-Chain Monte Carlo method with four chains. Each chain has 7000 iterations, with the first 3000 burned. A logit link function with bernoulli distribution over the parameters was used. A depended variable was evaluation if exposition time was closer to 400 or 1600 milliseconds. Model selection was made using *the expected log predictive density method* (Vehtari, Gelman, & Gabry, 2017).

In the first model, the null model was established. Then, random effects with a free intercept for each participant were added. In the second model, *Number Sense* and objective time were used as predictors. The second level residual variance was M = 0.02 (95% CI [<0.01, 0.05]). The model showed that *Number Sense* might predict duration estimation error. Higher score was associated with a M = 9.79% (95% CI [2.86%, 17.09%]) increase in the probability of correct classification. Additionally, there was a significant effect of objective time, which was associated with a M = 9.03% (95% CI [0.48%, 16.72%]) decrease in the probability of correct classification. A random effect of slope of objective time was M = 0.07 (95% CI [0.04, 0.13]). This model turned out to has the highest *elpd,* with R^2 of $M = 0.02$ (95% CI [0.02, 0.04]).

The third model included valence, arousal, and their interaction, along with random effects for these variables. Results showed that higher *Number Sense* was associated with $M =$ 10.18% (95% CI [3.15%, 17.58%]) increase in the probability of correct classification. Similarly, objec- CI [0.65%, 16.81%]) decrease in the probability of correct estimation.

In the final model, information theory variables were included. The previous effects were maintained, but no significant effects were found for valence, arousal, entropy, or luminance. Higher score of *Number Sense* was associated with M = 10.19% (95% CI [3.20%,

Table 3. Summary of models from experiment 3

	Model 1	***Model 2***	***Model 3***	***Model 4***
Predictors	*Est.* *[95% CI]*	*Est.* *[95% CI]*	*Est.* *[95% CI]*	*Est.* *[95% CI]*
Intercept	1.07 [1.00, 1.14]	1.09 [1.02, 1.15]	1.09 [1.02, 1.15]	1.09 [1.02, 1.15]
Number Sense		0.09 [0.03, 0.16]	0.10 [0.03, 0.16]	0.10 [0.03, 0.16]
Objective Time		-0.09 [-0.18, > -0.01]	-0.10 [-0.18, -0.01]	-0.10 [-0.19, -0.01]
Valance			>-0.01 [-0.05, 0.05]	>-0,01 [-0.06, 0.05]
Arousal			<0.01 [-0.06, 0.06]	>-0,01 [-0.05, 0.05]
Valence*Arousal			-0.02 [-0.03, 0.03]	-0.02 [-0.07, 0.03]
Entropy				-0.03 [-0.10, 0.05]
Luminance				0.03 [-0.04, 0.11]
ΔELPD [standard error]	-49.0 [8.1]	0.0 [0.0]	-4.9 [0.09]	-6.5 [1.3]
R^2	0.01	0.03	0.03	0.03

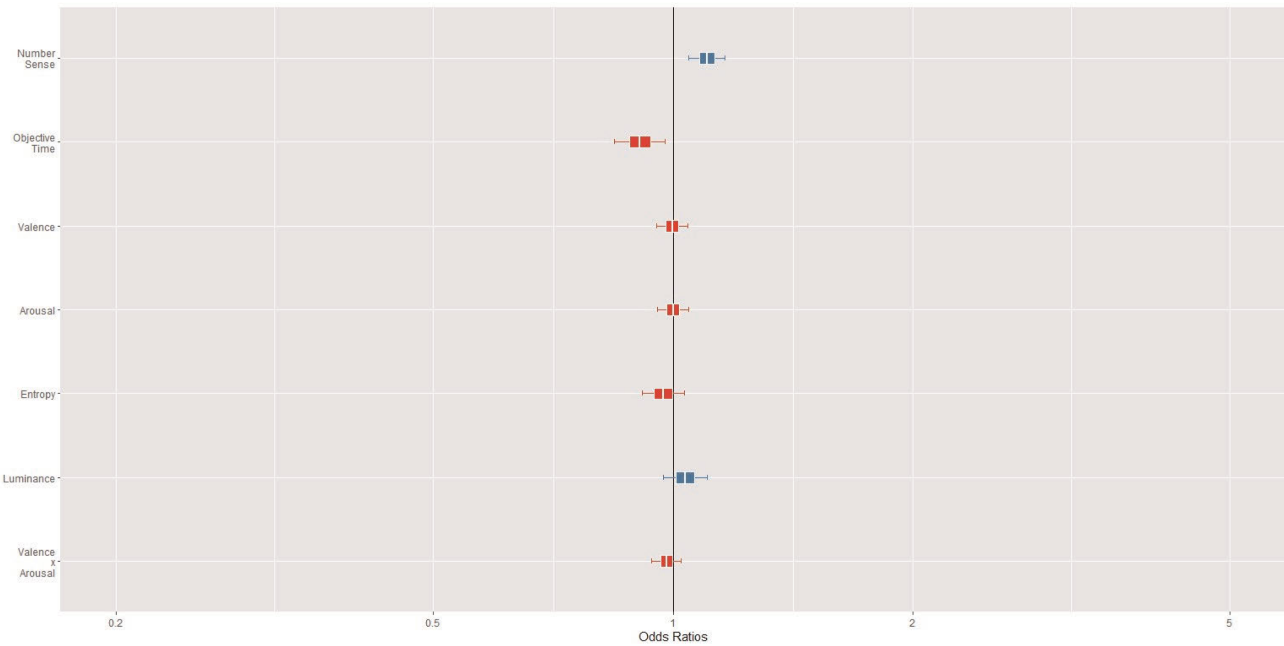

Fig 5. Posteriors of the final model for experiment no. 3

Objective exposition time was associated with M = 9.08% (95% CI [0.72%, 17.05%]) decrease in the probability of a correct answer. The final model had an R^2 of M = 0.03 (95% CI [0.02, 0.04]).

EXPERIMENT 4

Participants

The last study was conducted online. The worldwide COVID-19 pandemic situation forced this decision. Fifty-seven participants were recruited (28 female) using the Prolific system [www.prolific.co]. The mean age of participants was 25.93 (SD = 7.61). All participants were paid £9.00/hour. Additionally, they were restricted to a minimum of 80% approval rate, have a normal or corrected-to-normal vision, fluent English and participate in the study using a laptop or desktop. Study approval was granted by the University of the Ethics Board at the University of Social Sciences and Humanities.

Design and procedure

The final study aimed to address the core idea behind this paper. The method for examining subjective time distortion was identical to that in the first study, but this time, the procedure included additional variables intended to provide a deeper understanding of the *SET* model and evaluate potential extensions based on information-based features of stimuli.

Participants were asked to sit comfortably about 50 cm from the screen. Instructions were provided before each task. Prior to every stimulus (dots or pictures), participants saw a fixation point ("+"). The procedures were implemented using the PsychoJS library (Pierce, 2007) and Pavlovia (https://pavlovia.org/). To increase the reliability of the experiment, participants underwent a calibration process before the first stage. They were asked to adjust the image size of a credit card to match a real one, ensuring that all participants viewed stimuli of the same size.

The next part of the procedure for Experiment 4 was the measurement of Number Sense. To maintain consistency with Studies 1-3, magnitude comparisons were chosen to measure this variable. Participants were shown blue and yellow dots, with the size and location of the dots drawn randomly. The possible ratios of the numbers of dots were 3/4, 4/5, 5/6, and 6/7. After the dots disappeared, participants saw a mask (random yellow and blue noise). Following ten training trials, participants underwent 200 main trials.

After this phase, the time estimation stage began. Participants saw examples of the shortest (400 ms) and longest (1600 ms) exposition durations, followed by 14 training trials. In these trials, participants had to memorize a random string of 3-6 characters and estimate the duration for which a black box was visible. Answers were submitted using a slider. After this part, participants were asked to reproduce the random string. As affective stimuli, pictures from the NAPS database were used (Marchewka et al., 2014). The stimuli database was changed to provide a more reliable measurement for information theory variables. Both stages (Number Sense and time estimation) are shown in Figure 6.

Additional variables used in this study was memory overload described by Levenshtein distance (eq. 1) between generated and reproduced random string of signs.

$$\mathrm{lev}(a,b) = \begin{cases} |a| & \\ |b| & \mathrm{If}|b| = 0, \\ \mathrm{lev}(\mathrm{tail}(a), \mathrm{tail}(b)) & \mathrm{If}|a| = 0, \\ 1 + \min\begin{cases} \mathrm{lev}(\mathrm{tail}(a), b) \\ \mathrm{lev}(\mathrm{a}, \mathrm{tail}(b)) \\ \mathrm{lev}(\mathrm{tail}(a), \mathrm{tail}(b)) \end{cases} & \begin{matrix} \mathrm{If}a[0] = b[0] \\ \mathrm{otherwise}, \end{matrix} \end{cases}$$

Eq 1. Levenshtein distance

Moreover, pictures from the NAPS database (Marchewka et al., 2014) have described variables which were included in the analysis complexity considered as a JPEG size.

Results

Analogically to the previous experiments, the statistical analyses of multi-level Bayesian models using the brms package (Bürkner, 2017) in R (version 4.2.0) (R Core Team, 2022) were made. All models were fitted using the Markov-Chain Monte Carlo method with four chains. Each chain has 7000 iterations, with the first 3000 burned. Exactly like in study no. 1 and 2, predictors were standardized, and the dependent variable, estimation error (objective duration minus subjective duration), was defined. Model selection was made using *the expected log predictive density method* (Vehtari, Gelman, & Gabry, 2017).

In the first model, the null model with only free intercept was established. Additionally, random effects with free intercept for every participant were added. In the second model, *Number Sense* and objective time were used as predictors. The model showed no evidence that *Number Sense* could be considered a predictor of duration estimation error. However, there was a significant effect of objective time, M = -190.87 (95% CI [-209.52, -172.14]).

The third model included valence, arousal, and their interaction, along with random effects for valence, arousal, and their interaction. The effect of objective time remained significant, M = -191.57 (95% CI [-210.33, -172.47]). Furthermore, valence, arousal and valence:arousal interaction were not predictors of time estimation error.

In the final model, information theory variables were included. The first level residual variance is M = 33503.64 (95% CI [32421.60, 34640.65]). The second level residual variance is M = 14139.59 (95% CI [9735.77, 21068.52]). The results indicated that objective time was a significant negative predictor of time estimation error, M = -190.73 (95% CI [-209.56, -171.43]). Additionally, the Levenshtein distance emerged as a significant negative predictor, M = -14.70 (95% CI [-18.57, -10.77]). The results showed no significant effects for valence, arousal, or their interaction. A random effect of the slope was found in case of objective time M = 4944.90 (95% CI [3352.41,

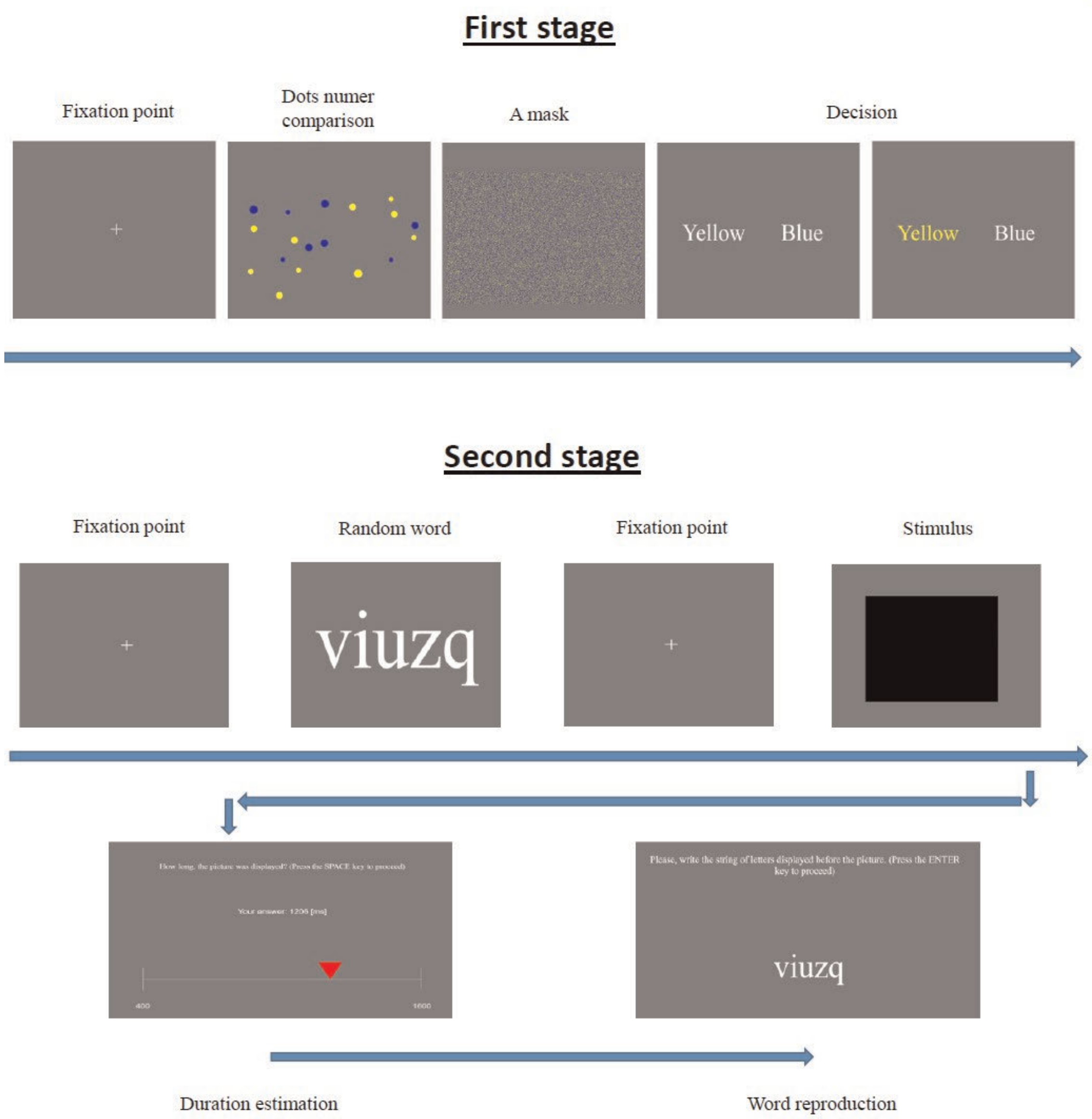

Table 4. Summary of models from experiment 4

	Model 1	*Model 2*	*Model 3*	*Model 4*
Predictors	*Est.* *[95% CI]*	*Est.* *[95% CI]*	*Est.* *[95% CI]*	*Est.* *[95% CI]*
Intercept	-135.89 [-166.92, -105.28]	-135.16 [-166.22, -104.48]	-133.05 [-163.75, -100.25]	-124.72 [-157.00, -93.37]
Number Sense		-15.96 [-46.87, 14.70]	-18.02 [-49.37, 12.66]	-18.89 [-50.41, 13.18]
Objective time		-190.87 [-209.52, -172.14]	-191.57 [-210.33, -172.47]	-190.73 [-209.56, -171.43]
Valence			5.16 [-6.75, 16.77]	4.76 [-7.13, 17.12]
Arousal			-7.67 [-19.24, 4.16]	-8.36 [-20.19, 3.51]
Valence x Arousal			2.77 [-3.43, 8.97]	2.65 [-3.55, 8.92]

Table 4 cont.

	Model 1	*Model 2*	*Model 3*	*Model 4*
Entropy				0.64 [-3.93, 5.24]
Luminance				-3.47 [-7.67, 0.79]
Complexity				-3.71 [-8.19, 0.70]
Levenshtein Distance				-14.70 [-18.57, -10.77]
ΔELPD [standard error]	-2920.1 [60.3]	-80.2 [16.0]	-26.9 [8.5]	0.0 [0.0]
R^2	0.14	0.61	0.62	0.62

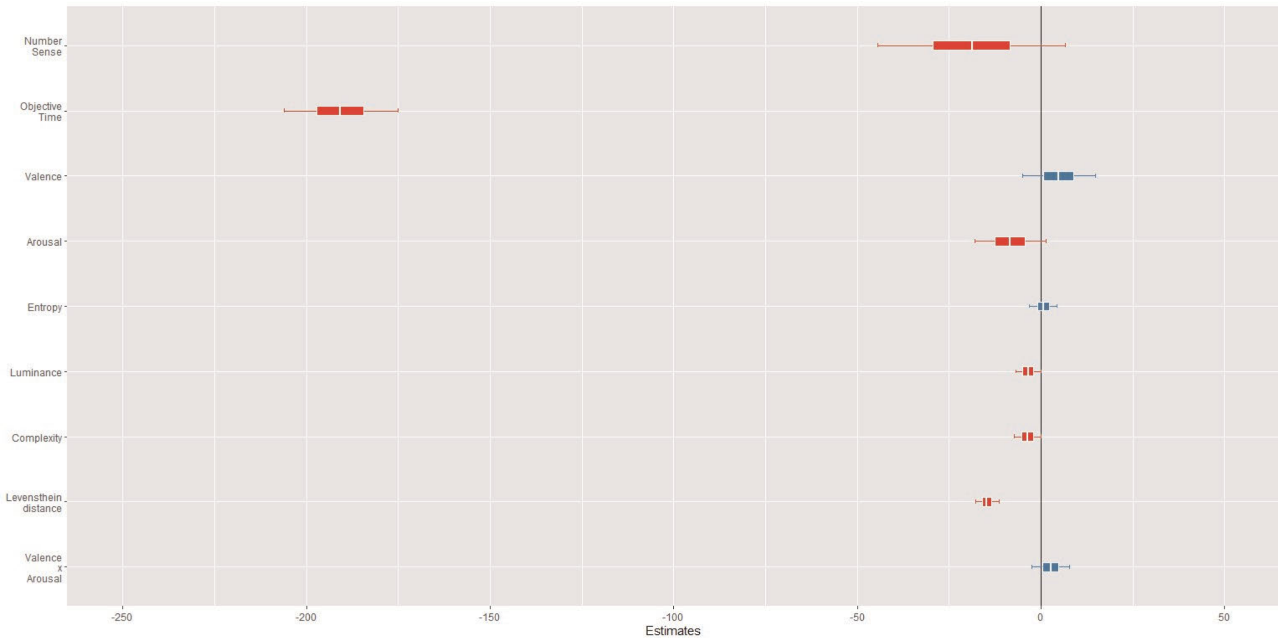

Fig 6. Procedure for experiment no. 4

7370.22]), valence M = 256.64 (95% CI [5.15, 824.26]) and arousal M = 242.11 (95% CI [3.65, 809.97]). The final model had an R^2 of 0.62 (95% CI [0.61, 0.63]) with the highest *elpd*.

CONCLUSION

The presented research had two primary objectives. The first was to highlight the complexity of human time perception and the insufficient exploration of its potential foundations, often constrained by long-established models and research paradigms. The second objective was to emphasize the opportunities available to researchers due to the rapidly advancing technology sector, particularly through leveraging information from fields such as Computer Vision.

All studies focused on time processing based on stimulus exposure in millisecond-to-second intervals. We grounded our research methodologies in well-established literature, ensuring the potential role of affect and valence induced by stimuli in each study (Angrilli et al., 1997; Noulhiane et al., 2007; Droit-Volet et al., 2004; Droit-Volet & Meck, 2007). Additionally, basic methods for measuring time exposure estimation were included. Due to the multitude of methods documented in the literature, it was impossible to examine the full spectrum, so we focused on the most well-researched and general methods, such as direct estimation using a slider, estimating stimulus exposure time by pressing a designated key for the duration the stimulus was visible on the screen, and classifying whether the stimulus was visible for closer to the minimum (400 ms) or the maximum (1600 ms) time. We also hypothesized that the performance of the *Approximate Number System* would be a significant predictor of time exposure estimation error. Finally, we extracted information-theoretic parameters from the stimuli, such as entropy and brightness, representing the complexity of the exposed stimuli.

In the first study, which closely followed the established paradigm of time perception research, participants estimated stimulus exposure time using a slider. The results partially aligned with known findings, showing an effect of valence. The more positive the picture, the longer it seemed to remain visible on the screen. Moreover, when considering the interaction of valence and arousal, for low-arousing stimuli, negative valence was associated with a shorter duration estimation compared to positive stimuli. For high-arousing stimuli, the effect was opposite. Additionally, our assumptions regarding the role of image complexity and brightness were confirmed. Entropy was a positive predictor of duration estimation, while luminance was a negative one. This means that the more information a picture contained, the higher the positive error in duration estimation, and the brighter the picture, the higher the negative duration estimation error. The most influential factor was the objective exposure time. The longer the picture was visible on the screen, the higher the underestimation of duration. Finally, participants' *Number Sense* (mean score in the magnitude comparison task) emerged as a negative predictor of duration estimation error. This subtle effect suggests that individuals with higher *Number Sense* tend to underestimate the duration of affective stimuli. While counterintuitive, it may indicate that time perception is based on information processing.

In the second study, the nature of stimulus exposure time estimation was altered. This time, participants responded by pressing a designated key for a duration as close as possible to the stimulus exposure time on the screen. This change resulted in Model 2, consisting solely of *Number Sense* and the objective stimulus duration as predictors, being the leading model. However, the *elpd* metric showed that differences between subsequent models were minimal, leading to a decision to further explore the role of potential predictors. Despite this, the only significant predictor was the objective stimulus exposure time. Known effects of valence, complexity, and brightness disappeared.

In the third study, a *Temporal Bisection Task* procedure was used, where participants classified stimulus exposure time as more similar to the shortest or longest possible time. The results were particularly interesting. *Number Sense* again emerged as a significant predictor. This time, the higher the participant's *Number Sense*, the more likely they were to classify correctly. The effect of objective exposure time persisted—the longer the picture was visible, the less likely the correct classification. Similar to Study 2, Model 2, which is simpler than the final model, emerged as the best model based on the *elpd* metric.

The final study included an additional element where working memory overload was measured, directly referring to the fundamental *SET* model. We also switched the stimulus database from IAPS (Lang, Bradley, & Cuthbert, 1997) to NAPS (Marchewka et al., 2014) to achieve the highest possible picture quality. This was based on our focus on information theory variables, which naturally depend on signal quality. The final model showed consistent conclusions for objective time. The longer the picture was visible on the screen, the higher the underestimation. Moreover, we found an effect of memory overload. The higher the Levenshtein distance (indicating worse word reproduction—lower memory overload), the higher the underestimation of exposure time. No other factor was considered a possible predictor of time estimation error.

In summary, the collected results appear chaotic and do not provide a direct answer to the research questions posed. However, they are valuable in considering the cognitive phenomenon of time perception in humans. As we see, when using basic methodologies, the effects described in the literature appear, but as soon as we introduce a modification unrelated to the exposure process but only to its evaluation, only the objective exposure time yields consistent results. This may suggest that the known effects in the literature are artifacts more related to the measurement characteristics than to the cognitive process being studied. Furthermore, this study demonstrates that bolder use of modern tools and incorporating variables from Computer Vision, Machine Learning, or even Large Language Models in the future can significantly enhance our understanding of how the human brain "sees" time. It is also worth mentioning that the classic SET model of time perception, based on the last study, seems overexplored in terms of the affective and valence characteristics of stimuli but underexplored in terms of the role of memory, which naturally emerges from its architecture. We cannot overlook that the studies were conducted during the COVID-19 pandemic, which caused significant organizational and methodological challenges. The last study was conducted online, which can be considered a drawback. This is a valid criticism because it complicates the comparison of conclusions drawn from the first three studies with the final one. Given the conclusion that the characteristics of the research procedure can generate artifacts, it is difficult to determine whether it is justified to compare the results of these studies with each other. However, this is inevitable in research on such a complex and delicate process, requiring collective efforts to verify the described results across a broader spectrum of experimental procedures on time perception and standardizing research conditions (which could not be maintained due to the pandemic).

REFERENCES

Agrillo, C., Piffer, L. & Adriano, A. Individual differences in non-symbolic numerical abilities predict mathematical achievements but contradict ATOM. Behav Brain Funct 9, 26 (2013). https://doi.org/10.1186/1744-9081-9-26

Angrilli, A., Cherubini, P., Pavese, A. et al. The influence of affective factors on time perception. Perception & Psychophysics 59, 972–982 (1997). https://doi.org/10.3758/BF03205512

Bajammal, M., Stocco, A., Mazinanian D. and Mesbah A., "A Survey on the Use of Computer Vision to Improve Software Engineering Tasks" in IEEE Transactions on Software Engineering, vol. 48, no. 5, pp. 1722-1742, 1 May 2022, doi: 10.1109/TSE.2020.3032986

Bilgili, B., Ozkul, E., & Koc, E. (2018). The influence of colour of lighting on customers' waiting time perceptions. Total Quality Management & Business Excellence, 31(9–10), 1098–1111. https://doi.org/10.1080/14783363.2018.1465814

Brannon, E. M., & Merritt, D. J. (2011). Evolutionary foundations of the approximate number system. Space, time and number in the brain, Academic Press, 2011, Pages 207-224, ISBN 9780123859488, https://doi.org/10.1016/B978-0-12-385948-8.00014-1.

van Bueren NER, van der Ven SHG, Roelofs K, Cohen Kadosh R, Kroesbergen EH. Predicting Math Ability Using Working Memory, Number Sense, and Neurophysiology in Children and Adults. *Brain Sciences*. 2022; 12(5):550. https://doi.org/10.3390/brainsci12050550

Burra, N., & Kerzel, D. (2021). Meeting another's gaze shortens subjective time by capturing attention. *Cognition*, 212, https://doi.org/10.1016/j.cognition.2021.104734.

Cheyette, S.J., Piantadosi, S.T. A unified account of numerosity perception. *Nat Hum Behav* 4, 1265–1272 (2020). https://doi.org/10.1038/s41562-020-00946-0

Cui, X., Tian, Y., Zhang, L. et al. The role of valence, arousal, stimulus type, and temporal paradigm in the effect of emotion on time perception: A meta-analysis. *Psychon Bull Rev* 30, 1–21 (2023). https://doi.org/10.3758/s13423-022-02148-3

Danckert, J. A., & Allman, A. A. A. (2005). Time flies when you're having fun: Temporal estimation and the experience of boredom. *Brain and cognition*, 59(3), 236-245. https://doi.org/10.1016/j.bandc.2005.07.002.

Dehaene, S. (2011). The number sense: How the mind creates mathematics. *OUP USA*.

DeWind, N. K., Adams, G. K., Platt, M. L., & Brannon, E. M. (2015). Modeling the approximate number system to quantify the contribution of visual stimulus features. *Cognition*, 142, 247-265. https://doi.org/10.1016/j.cognition.2015.05.016.

Dietrich, J. F., Huber, S., & Nuerk, H. C. (2015). Methodological aspects to be considered when measuring the approximate number system (ANS) - a research review. *Frontiers in psychology*, 6, 295. https://doi.org/10.3389/fpsyg.2015.00295

Droit-Volet, S., & Berthon, M. (2017). Emotion and Implicit Timing: The Arousal Effect. *Frontiers in psychology*, 8, 176. https://doi.org/10.3389/fpsyg.2017.00176

Droit-Volet, S., & Gil, S. (2009). The time-emotion paradox. Philosophical transactions of the Royal Society of London. Series B, Biological sciences, 364(1525), 1943–1953. https://doi.org/10.1098/rstb.2009.0013

Droit-Volet, S., & Gil, S. (2016). The emotional body and time perception. Cognition & emotion, 30(4), 687–699. https://doi.org/10.1080/02699931.2015.1023180

Droit-Volet, S., & Meck, W. H. (2007). How emotions colour our perception of time. Trends in cognitive sciences, 11(12), 504–513. https://doi.org/10.1016/j.tics.2007.09.008

Droit-Volet, S., & Wearden, J. H. (2001). Temporal bisection in children. Journal of experimental child psychology, 80(2), 142–159. https://doi.org/10.1006/jecp.2001.2631

Eagleman D. M. (2008). Human time perception and its illusions. Current opinion in neurobiology, 18(2), 131–136. https://doi.org/10.1016/j.conb.2008.06.002

Fayolle, S., Gil, S., & Droit-Volet, S. (2015). Fear and time: Fear speeds up the internal clock. Behavioural processes, 120, 135–140. https://doi.org/10.1016/j.beproc.2015.09.014

Fazio, L. K., Bailey, D. H., Thompson, C. A., & Siegler, R. S. (2014). Relations of different types of numerical magnitude representations to each other and to mathematics achievement. Journal of experimental child psychology, 123, 53–72. https://doi.org/10.1016/j.jecp.2014.01.013

Gibbon, J. (1977). Scalar expectancy theory and Weber's law in animal timing. Psychological Review, 84(3), 279–325. https://doi.org/10.1037/0033-295X.84.3.279

Gibbon, J., Church, R.M., & Meck, W.H. (1984). Scalar Timing in Memory. Annals of the New York Academy of Sciences, 423.

Gil, S., Niedenthal, P. M., & Droit-Volet, S. (2007). Anger and time perception in children. Emotion (Washington, D.C.), 7(1), 219–225. https://doi.org/10.1037/1528-3542.7.1.219

Gilliland, A. R., Hofeld, J., & Eckstrand, G. (1946). Studies in time perception. Psychological bulletin, 43, 162–176. https://doi.org/10.1037/h0062512

Gilmore, C., Attridge, N., & Inglis, M. (2011). Measuring the approximate number system. Quarterly journal of experimental psychology (2006), 64(11), 2099–2109. https://doi.org/10.1080/17470218.2011.574710

Gilmore, C. K., McCarthy, S. E., & Spelke, E. S. (2010). Non-symbolic arithmetic abilities and mathematics achievement in the first year of formal schooling. Cognition, 115(3), 394–406. https://doi.org/10.1016/j.cognition.2010.02.002

Grondin S. (2010). Timing and time perception: a review of recent behavioral and neuroscience findings and theoretical directions. Attention, perception & psychophysics, 72(3), 561–582. https://doi.org/10.3758/APP.72.3.561

Guillaume, M., Gevers, W., & Content, A. (2016). Assessing the Approximate Number System: no relation between numerical comparison and estimation tasks. Psychological research, 80(2), 248–258. https://doi.org/10.1007/s00426-015-0657-x

Halberda, J., Mazzocco, M. M., & Feigenson, L. (2008). Individual differences in non-verbal number acuity correlate with maths achievement. Nature, 455(7213), 665–668. https://doi.org/10.1038/nature07246

Javadi, A. H., Brunec, I. K., Walsh, V., Penny, W. D., & Spiers, H. J. (2014). Transcranial electrical brain stimulation modulates neuronal tuning curves in perception of numerosity and duration. NeuroImage, 102 Pt 2, 451–457. https://doi.org/10.1016/j.neuroimage.2014.08.016

Krahn, E. (2018). Decomposing the effect of color on memory: How red and blue affect memory differently.

Kroesbergen, E. H., & Van Dijk, M. (2015). Working memory and number sense as predictors of mathematical (dis-) ability. *Zeitschrift für Psychologie*, 223(2), 102. https://doi.org/10.1027/2151-2604/a000208

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1997). International affective picture system (IAPS): Technical manual and affective ratings. *NIMH Center for the Study of Emotion and Attention*, 1(39-58), 3.

Lang, P.J., Bradley, M.M., & Cuthbert, B.N. (2008). International affective picture system(IAPS): Affective ratings of pictures and instruction manual. Technical Report A-8. University of Florida, Gainesville, FL.

Lee, H. Y., & Yang, E. L. (2019). Exploring the Effects of Working Memory on Time Perception in Attention Deficit Hyperactivity Disorder. Psychological reports, 122(1), 23–35. https://doi.org/10.1177/0033294118755674

Leon, M. I., & Shadlen, M. N. (2003). Representation of time by neurons in the posterior parietal cortex of the macaque. Neuron, 38(2), 317–327. https://doi.org/10.1016/s0896-6273(03)00185-5

Marchewka, A., Zurawski, Ł., Jednoróg, K., & Grabowska, A. (2014). The Nencki Affective Picture System (NAPS): introduction to a novel, standardized, wide-range, high-quality, realistic picture database. Behavior research methods, 46(2), 596–610. https://doi.org/10.3758/s13428-013-0379-1

Meck, W. H., & Church, R. M. (1983). A mode control model of counting and timing processes. Journal of experimental psychology. Animal behavior processes, 9(3), 320–334.

Meck, W. H., Penney, T. B., & Pouthas, V. (2008). Cortico-striatal representation of time in animals and humans. Current opinion in neurobiology, 18(2), 145–152. https://doi.org/10.1016/j.conb.2008.08.002

Noulhiane, M., Mella, N., Samson, S., Ragot, R., & Pouthas, V. (2007). How emotional auditory stimuli modulate time perception. Emotion (Washington, D.C.), 7(4), 697–704. https://doi.org/10.1037/1528-3542.7.4.697

Pan, Y., & Luo, Q. Y. (2012). Working memory modulates the perception of time. Psychonomic bulletin & review, 19(1), 46–51. https://doi.org/10.3758/s13423-011-0188-4

Park, J., & Brannon, E. M. (2013). Training the approximate number system improves math proficiency. Psychological science, 24(10), 2013–2019. https://doi.org/10.1177/0956797613482944

Peirce J. W. (2007). PsychoPy–Psychophysics software in Python. Journal of neuroscience methods, 162(1-2), 8–13. https://doi.org/10.1016/j.jneumeth.2006.11.017

Piaget, J. (1953). The Child's Conception of Number. British Journal of Educational Studies 1 (2):183-184. DOI: 10.2307/3118763

Piazza, M., Pica, P., Izard, V., Spelke, E. S., & Dehaene, S. (2013). Education enhances the acuity of the nonverbal approximate number system. Psychological science, 24(6), 1037–1043. https://doi.org/10.1177/0956797612464057

Pöppel, E. (1978). Time perception. In Perception (pp. 713-729). Springer, Berlin, Heidelberg. DOI: 10.1007/978-1-4899-6771-8_49.

Qian, J., Zhang, K., Wang, K., Li, J., & Lei, Q. (2018). Saturation and brightness modulate the effect of depth on visual working memory. Journal of vision, 18(9), 16. https://doi.org/10.1167/18.9.16

Roy, M., Grondin, S., & Roy, M. A. (2012). Time perception disorders are related to working memory impairment in schizophrenia. Psychiatry research, 200(2-3), 159–166. https://doi.org/10.1016/j.psychres.2012.06.008

Van de Rijt, B., Godfrey, R., Aubrey, C., van Luit, J. E., Ghesquière, P., Torbeyns, J., ... & Tzouriadou, M. (2003). The Development of Early Numeracy in Europe. Journal of Early Childhood Research. 1. https://doi.org/10.1177/1476718X030012002

Sasanguie, D., De Smedt, B., Defever, E., & Reynvoet, B. (2012). Association between basic numerical abilities and mathematics achievement. The British journal of developmental psychology, 30(Pt 2), 344–357. https://doi.org/10.1111/j.2044-835X.2011.02048.x

Schneider, M., Beeres, K., Coban, L., Merz, S., Susan Schmidt, S., Stricker, J., & De Smedt, B. (2017). Associations of non-symbolic and symbolic numerical magnitude processing with mathematical competence: a meta-analysis. Developmental science, 20(3), https://doi.org/10.1111/desc.12372

Smets, K., Gebuis, T., & Reynvoet, B. (2013). Comparing the neural distance effect derived from the non-symbolic comparison and the same-different task. Frontiers in human neuroscience, 7, 28. https://doi.org/10.3389/fnhum.2013.00028

Thomas, E. A., & Weaver, W. B. (1975). Cognitive processing and time perception. Perception & Psychophysics. 17. 363-367. https://doi.org/10.3758/BF03199347

Thönes, S., von Castell, C., Iflinger, J., & Oberfeld, D. (2018). Color and time perception: Evidence for temporal overestimation of blue stimuli. Scientific reports, 8(1), 1688. https://doi.org/10.1038/s41598-018-19892-z

Thönes, S., & Oberfeld, D. (2015). Time perception in depression: a meta-analysis. Journal of affective disorders, 175, 359–372. https://doi.org/10.1016/j.jad.2014.12.057

Toll, S. W., Kroesbergen, E. H., & Van Luit, J. E. (2016). Visual working memory and number sense: Testing the double deficit hypothesis in mathematics. The British journal of educational psychology, 86(3), 429–445. https://doi.org/10.1111/bjep.12116

Tramacere, A., Allen, C. Temporal binding: digging into animal minds through time perception. Synthese 200, 1 (2022). https://doi.org/10.1007/s11229-022-03456-w

Üstün, S., Kale, E. H., & Çiçek, M. (2017). Neural Networks for Time Perception and Working Memory. Frontiers in human neuroscience, 11, 83. https://doi.org/10.3389/fnhum.2017.00083

Walsh V. (2003). Time: the back-door of perception. Trends in cognitive sciences, 7(8), 335–338. https://doi.org/10.1016/s1364-6613(03)00166-9

Woodrow, H. (1951). Time perception. In S. S. Stevens (Ed.), Handbook of experimental psychology (pp. 1224–1236). Wiley.

Vehtari, A., Gelman, A., and Gabry, J. (2017a). Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. *Statistics and Computing*. 27(5), 1413–1432. doi:10.1007/s11222-016-9696-4

Yamada, Y., & Kawabe, T. (2011). Emotion colors time perception unconsciously. Consciousness and cognition, 20(4), 1835–1841. https://doi.org/10.1016/j.concog.2011.06.016