UNIVERSITAT DE BARCELONA

All Times at Once: Multiple Timing and Uncertainty in Time Perception

Jaume Boned Garau

ALL TIMES AT ONCE:

Multiple Timing and uncertainty in time perception.

JAUME BONED GARAU

ALL TIMES AT ONCE: MULTIPLE TIMING AND UNCERTAINTY IN TIME PERCEPTION

by

Jaume Boned Garau

Submitted for the degree of Doctor in Philosophy

Doctoral Program in Brain, Cognition and Behaviour

Vision and Control of Action Group

Department of Cognition, Development and Educational Psychology

University of Barcelona

Supervised by:

Prof. Dr. Joan López-Moliner

Barcelona, 2024

ACKNOWLEDGEMENTS

Some while ago I made a decision that brought me to dedicate the last years to one of the most challenging things I have faced, but neither did I start this journey alone, nor could have I made it so far without the support of so many people. This is the part where I do my best to express my gratitude to them.

Per començar, Joan, gràcies per tot el suport i per guiar-me durant tot aquest camí. Gràcies per escoltar-me amb paciència tots els cops que venia al teu despatx amb una idea al cap, potser massa desbaratada, però sense mai descartar-ne cap. Gràcies per donar-me la llibertat de perseguir les meves pròpies idees i per ajudar-me a capgirar-les i convertir-les en quelcom factible, pràctic i amb sentit, en un camí a seguir. M'has ajudat a aprendre a veure la ciència amb uns ulls diferents, a sortir de la meva zona de confort i a obligar-me a aprendre a fer les coses millor. Sense aquesta ajuda sé que la tesi no hauria tingut la rellevància que ara mateix sento que té.

De la mateixa manera, vull agrair a tots els membres del VISCA que m'hàgiu permès formar part d'aquesta petita família. Cristina, gràcies per tots els teus consells i per donar-me la teva visió sobre els meus projectes cada cop que t'ho demanava, clarament m'has ajudat més que ningú a detectar aquelles petites coses que converteixen un projecte en la seva millor versió. Però sobretot, gràcies per ensenyar-me a ensenyar. Dani, gracias por los ratos que hemos compartido desde que te uniste de nuevo a la facultad. Antes de conocerte me sorprendió el cariño que te tenía todo el mundo, ahora lo entiendo perfectamente. Gracias por tus comentarios sinceros, sin cortarte un pelo pero siempre constructivos. Espero encontrar gente tan transparente e inteligente en el futuro.

Por supuesto, Borja, definitivamente esta tesis no habría sido la misma si no hubiésemos coincidido. Has sido el ejemplo más cercano al que he podido seguir los pasos. Unos pasos cuyas huellas siempre he sentido que no conseguía llenar, pero que el simple hecho de intentar seguirlas ya me ha hecho acercarme a ser un mejor científico. Gracias por todo el apoyo en los momentos más complicados, por ayudarme a mantener la calma y a entender muchas cosas, y también por ayudarme a mantener los pies en el suelo y darme cuenta de cuándo necesitaba ponerme las pilas. Pero sobre todo, gracias por ser un gran amigo.

En cuanto a la siguiente generación, Pam, Cristina, Andrés y Cristian, ojalá haber podido compartir más tiempo con vosotros, pero he disfrutado cada segundo. Solo espero haber podido aportaros por lo menos una fracción de todo lo que yo recibí y haber allanado el principio del camino. No tengo ninguna duda de que al paso que vais tendréis un futuro más que brillante. Sobre todo, gracias por hacerme revivir esos primeros años de la tesis, veros llenos de energía, de ideas, de entusiasmo me ha ayudado a recuperar la motivación en los momentos más frustrantes. No puedo esperar a ver a dónde os llevan vuestros caminos.

También quiero agradecer a toda la gente del departamento que ha convertido un simple lugar de trabajo en un espacio familiar que se sentía como una segunda casa. Àngels, Javier, Cristina Baus, Joanna gracias por todas las comidas entretenidas, por hacerme sentir uno más y por ayudarme a conocer un poco mejor el mundo académico desde otras perspectivas. Elisabet, gràcies per tenir la paciència amb nosaltres quan d'un dia per l'altre vem envair el despatx, i així i tot no ens podríem haver sentit més ben rebuts.

Gracias a Gema y Asier, por darme las herramientas para levantarme cada vez que me caiga, y darme cuenta de con trabajo y perspectiva no hay catástrofe que valga.

To Prof. Alan Johnston, thank you for having at Nottingham, and for carefully listening and discussing my ideas. Also, thanks to all the people who made me feel as comfortable as possible during those months there.

També vull aprofitar per agrair a aquelles persones que fins i tot abans d'iniciar el doctorat ja van deixar una empremta en mi i em van ajudar a trobar el meu lloc al món de la recerca.

Als Hurakans Puntuals, sense vosaltres no hauria ni començat aquest viatge. Gràcies per obrir-me les portes de la recerca i contagiar-me amb el virus de la passió per la psicologia bàsica, i en especial, Judit, gràcies per descobrir-me el món tan fascinant i alhora el repte tan difícil que és la percepció del temps. I sobretot, gràcies per fer-me sentir un científic més quan encara em sentia tan petit un món massa complex.

Mireia, gràcies per prendre el relleu d'aquest rol i continuar motivant-me en la recerca. Va ser un orgull i, tot i breu, vaig gaudir de poder treballar amb tu i poder contribuir a un camp del qual no coneixia tant, però que ara em sembla profundament interessant.

A totes les companyes i companys amb qui he compartit aquest camí durant tants anys i han acabat convertint-se en molt més que això. Vàrem començar pràcticament junts i ara sembla mentida, però a poc a poc anem acabant. Marc D., Laura, Laia, Carlos, Marta, Joan, Gemma, Marc S., Martina, Stella, i a tots els refugiats del 3515, gràcies per formar part de la meva vida, de compartir penúries i de fer-me riure tants cops. Heu estat un gran suport en aquests anys, tant en l'àmbit laboral com a nivell personal. Em sento extremadament afortunat d'haver coincidit amb vosaltres i d'haver creat un vincle tan fort. Tant de bo ens continuem trobant dintre o fora de la acadèmia.

Adri, aquest camí l'he recorregut amb tu més que amb ningú altre, gràcies per sempre estar disposat a donar-me un cop de mà, i per obrir-me a un món que desconeixia, però que m'ha aportat tant durant els darrers anys. Que puguem compartir moltes més aventures.

A la família Francachella, Eva, Clara i Candela, gràcies per acollir-me quan estava perdut, per escoltar-me i per tots els moments fantàstics que hem compartit i que encara compartirem. Nora, sento que sempre m'has tingut en un pedestal que no m'he guanyat, però t'agraeixo la confiança que has tingut en mi.

Gràcies a ses persones que han cregut en jo més de lo que jo mateix era capaç. A en Johannes, que sempre que em preguntaves coses d'es mon científic i m'has escoltat amb una atenció sincera i amb una curiositat refrescant. A es meus pares Kati i Pepe, que sempre m'heu donat suport en tot lo que he intentat fer i sempre m'heu vist amb es millors ulls, gràcies per estar sempre pendents. I per últim, Cintia, gràcies per fer lo més difícil de tot, lo que ningú més ha pogut fer, ajudar-me a confiar en jo mateix i aguantar-me tot es camí. Gràcies per estar sempre en es meu costat i no deixar que em rendís.

The work presented in this thesis was supported by the fellowship FPU20/01368 from Ministerio de Educacion y Formacion Profesional of the Spanish government and by grant PID2020-114713GB-I00 funded by MCIN/AEI/10.13039/50110001103.

SUMMARY

In our daily lives, we often navigate situations that require us to manage multiple temporal intervals simultaneously. Whether it is timing the cooking times of different ingredients when preparing a meal, playing a musical instrument, and synchronizing with other musicians while keeping track of your own tempo, or driving in busy traffic and paying attention to the timing of traffic lights, crossing pedestrians, and the paths of vehicles, our ability to accurately perceive and measure time is crucial. These are just some of the many examples that illustrate the complexity of real-life tasks in which our perception of time enables us to navigate time-sensitive environments effectively.

The present thesis investigates the cognitive processes involved in time perception, focusing especially on how we manage multiple temporal intervals simultaneously and how uncertainty influences these processes. By exploring these dynamics, our research aims to deepen our understanding of the mechanisms that enable us to function effectively in such situations. To this aim, we developed three studies that combine theoretical modelling, empirical research, and the development of new tools to investigate these mechanisms.

Throughout the various studies that constitute the thesis, we address the challenge of simultaneous multiple timing from different perspectives:

In the first study, understanding multiple timings as a source of interference, we translated a common size illusion to the temporal domain, which allowed us to measure how distractors can distort the perceived duration of an attended event. We found a clear influence of surrounding stimuli duration on the perceived duration an attended event, although not in the same direction as the effects of the same type of paradigm in the visuo-spatial modality.

On the other hand, the second study explored multiple timing as an ability for managing complex tasks. We designed a novel experimental task to explore the optimality of human observers in simulated real-life scenarios that require a certain capacity of tracking, measuring, and working with multiple durations at the same time. We found that, although in an only partially optimal manner, participants utilized the multiple simultaneous sources of temporal information to guide their behaviour.

Our findings contribute to refining existing models of time perception by extending them to better account for the complexities of simultaneous multiple timing, as well as developing new models or methods to fill the gaps in less explored paradigms. Additionally, our third study introduces and validates an innovative methodology designed to measure temporal uncertainty more accurately and without the caveats that more traditional methods entail, thereby enhancing our ability to study these cognitive processes in greater detail. This method also offers new insights into the cognitive processes underlying uncertainty in time perception, providing a valuable tool for future research and practical applications.

Overall, the present thesis advances our understanding of time perception by investigating the complex interactions between simultaneous temporal intervals encompassed in both sub-second and supra-second ranges, as well as the critical role of uncertainty in such situations. By refining existing models and introducing new methodologies, the research sheds light on the cognitive processes that underpin our ability to manage multiple timing tasks. The insights gained from this work not only reinforce the theoretical foundations of time perception but also provide practical tools for future studies to further explore how we perceive and process time under real-world conditions. These contributions lay a foundation for continued research in this area, with potential implications for fields ranging from cognitive psychology to applied technologies where precise timing is critical.

RESUMEN

En nuestra vida diaria, constantemente nos enfrentamos a situaciones que requieren gestionar múltiples intervalos de tiempo simultáneamente. Ya sea cronometrando los tiempos de cocción de diferentes ingredientes al preparar una comida, tocando un instrumento musical y sincronizándonos con otros músicos mientras mantenemos nuestro propio ritmo, o conduciendo en un tráfico denso y prestando atención a los cambios de los semáforos, los peatones que cruzan y las trayectorias de otros vehículos, nuestra capacidad de percibir y medir el tiempo con precisión es crucial. Estos son solo algunos de los muchos ejemplos que ilustran la complejidad de las tareas cotidianas en las que nuestra percepción del tiempo nos permite resolver eficazmente situaciones donde el tiempo es un factor clave.

La presente tesis investiga los procesos cognitivos involucrados en la percepción del tiempo, centrándose especialmente en cómo medimos múltiples intervalos de tiempo simultáneamente y cómo la incertidumbre influye en estos procesos. Al explorar estas dinámicas, nuestra investigación busca profundizar en la comprensión de los mecanismos que nos permiten funcionar eficazmente en tales situaciones. Para ello, desarrollamos tres estudios en los que se combina el planteamiento de modelos computacionales, la investigación empírica y el desarrollo de nuevas herramientas que faciliten la medición de dichos procesos.

A lo largo de los distintos estudios que componen la tesis, abordamos el desafío de entender cómo percibimos múltiples intervalos de tiempo simultáneos desde distintas perspectivas:

En el primer estudio, en el que se entiende la percepción de múltiples duraciones simultáneas como una fuente de interferencia, se adapta una conocida ilusión de tamaño al dominio temporal. Esto nos permitió medir cómo distractores simultáneos pueden distorsionar la duración percibida de un evento atendido. Se encontró una influencia clara de los estímulos simultáneos, aunque no en la misma dirección que los efectos encontrados en el mismo tipo de paradigma en el dominio espaciotemporal.

Por otro lado, el segundo estudio explora la percepción de múltiples intervalos como una habilidad para resolver tareas complejas. Se diseñó una nueva tarea

experimental para explorar la capacidad humana de resolver tareas en escenarios simulados de la vida real que requieren cierta capacidad de medir, seguir y trabajar con múltiples duraciones al mismo tiempo. Los resultados muestran que, aunque de una forma solo parcialmente óptima, los participantes fueron capaces de utilizar las múltiples fuentes de información temporal simultáneas para guiar su comportamiento.

Nuestros hallazgos contribuyen a refinar los modelos existentes de percepción del tiempo, extendiéndolos para comprender mejor las complejidades de la percepción de tiempo con múltiples intervalos, así como desarrollar nuevos modelos o métodos para llenar los vacíos en paradigmas menos explorados.

Además, nuestro tercer estudio introduce y valida metodologías innovadoras diseñadas para medir la incertidumbre en medidas de tiempo con mayor precisión y sin las limitaciones de los métodos tradicionales., lo que mejora nuestra capacidad de estudiar estos procesos cognitivos con más detalle. Este método también aporta nuevas perspectivas sobre los procesos cognitivos que subyacen a la incertidumbre en la percepción del tiempo, proporcionando una herramienta valiosa para futuras investigaciones y aplicaciones prácticas.

En resumen, la presente tesis avanza en nuestra comprensión de la percepción del tiempo al investigar las complejas interacciones entre intervalos de tiempo simultáneos incluyendo duraciones tanto superiores como inferiores a un segundo, así como el papel crucial de la incertidumbre en dichas situaciones. Al refinar modelos existentes e introducir nuevas metodologías, la investigación arroja luz sobre los procesos cognitivos que sustentan nuestra capacidad para gestionar tareas que requieren controlar varios intervalos de tiempo simultáneos. Los conocimientos obtenidos de este trabajo no solo refuerzan las bases teóricas de la percepción del tiempo, sino que también proporcionan herramientas prácticas para futuros estudios que exploren cómo percibimos y procesamos el tiempo en condiciones del mundo real. Estas contribuciones sientan las bases para investigaciones continuas en esta área, con posibles implicaciones en campos que van desde la psicología cognitiva hasta las tecnologías aplicadas donde la precisión en la medición de tiempo es fundamental.

TABLE OF CONTENTS

Part I

GENERAL INTRODUCTION

GENERAL INTRODUCTION

Time perception is a fundamental aspect of human cognition that plays a critical role in a wide range of everyday activities and behaviours. It influences how we interact with the world, from making split-second decisions to planning long-term goals.

For example, when queuing at a supermarket, we might constantly wonder if another line would move faster. Similarly, while using a computer, we assess if a loading process has taken too long to decide if the system might have crashed. Waiting in various settings like hospitals, airports, or during a commute can feel particularly tedious, while engaging in enjoyable activities often makes time seem to fly by. These common situations highlight how our perception of the passage of time can impact a significant portion of our daily lives.

Beyond these everyday scenarios, time perception becomes even more critical in situations that require precise actions and quick decisions. For instance, athletes in many sports often rely on accurate time perception to synchronize their movements and reactions. On a more frequent example, judging the time we have to cross a street involves complex time estimations based on the oncoming traffic, and similarly, when driving, our ability to perceive and react to changing conditions on the road becomes vital for our safety. These scenarios underscore the importance of accurate time perception for successful and safe actions, highlighting its role not only in how we experience the world but also in how we interact with it, from predicting movements and intercepting objects to understanding speech and engaging in social interactions. By understanding time perception, we can better grasp how humans navigate and interpret the temporal aspects of their environment, making it a key component in understanding human cognition and behaviour.

However, although its influence is quite evident, defining time perception poses a challenge. To begin with, the definition of physical time itself is still unclear. Despite its apparent linearity, it is hard to give a definition without circularity. An example closer to philosophy that we could settle for is the pragmatic definition of “time is what the clock says.” This grounds the definition of time under its own measure, and we can do the same to understand time perception just by putting ourselves in place of the clock. Therefore, time perception is what we are measuring, the process itself of sensing, estimating, and evaluating time intervals from the millisecond range to days or even longer. That said, research in time perception focuses on understanding and describing this process.

However, unlike other perceptual systems, it faces a significant obstacle: this system lacks a sensory organ to capture this type of information from an external source, unlike how we have eyes and ears to convert light stimulation and sound waves into neural signals. This absence makes it considerably more challenging to understand how we generate these types of mental representations and makes it crucial to ascertain which sources of information we utilise for this purpose. Despite this, research in time perception has revealed very diverse factors can influence how we measure and judge time, including for example temporal frequency and motion, stimulus intensity and salience, task relevance and attention, emotional significance and arousal, stimulus familiarity and expectation, cognitive load and secondary tasks, contextual factors and relative magnitude, and neural mechanisms such as dopamine levels and prefrontal cortex activity (Buhusi & Meck, 2005; Kanai et al., 2006; Matthews & Meck, 2016; Vatakis et al., 2018; J. Wearden, 2016),

With this, the urge of many researchers to give an answer to how we measure and perceive time led to the development of numerous models and theories aimed at explaining the underlying mechanisms that support this ability (Addyman et al., 2016).

MODELS OF TIME PERCEPTION

Although the study of time perception has its roots in early psychological and physiological research, with pioneers like Wilhelm Wundt and William James already exploring the subjective experience of time and its relationship to sensory and cognitive processes, it was not until the mid-20th century that more formalized models began to emerge.

Internal Clock Models

Pacemaker-Accumulator Model

One of the first formal models of time perception was the pacemaker-accumulator (PA) model, which remains probably one of the most influential models in the field to this day. With their initial formulations by Creelman and Treisman (Creelman, 1962; Treisman, 1963), the PA model describes a dedicated centralized model for temporal processing that measures time in a linear or metric way, similar to a stopwatch. The structure of the model is divided into a series of components that are mostly common to the different variations of the model and cover the various stages required to measure an interval and generate a response according to it.

The timing process starts with a pacemaker that emits pulses at a constant rate. Although, the rhythm of this pacemaker can vary depending on the arousal level. In Treisman's model, higher arousal leads to increased speed of the pacemaker, resulting in more pulses being generated over a given physical duration, which could end up biasing the estimation of such duration.

Then, these pulses are collected in an accumulator component that counts the quantity of pulses that got through since the onset of the event. This count value is what will represent the raw measure of interval duration in the mental space and will be sent to a comparator component where it will be compared against previously stored values in memory.

Finally, this comparison allows us to assign verbal labels to deliver an estimate of the duration or engage in a behavioural response according to the end of that event. This response as a product of perceptual judgment has been widely explored empirically using paradigms such as comparison or judgment tasks (where responses depend on whether the accumulated pulses reach a certain threshold) or estimation tasks (where a response is delivered by behaviourally putting an end to the interval when enough pulses have been accumulated or by delivering an external representation of the number of pulses accumulated during that period). Figure 1.1 illustrates the process by showing how the information travels from one component to the other.

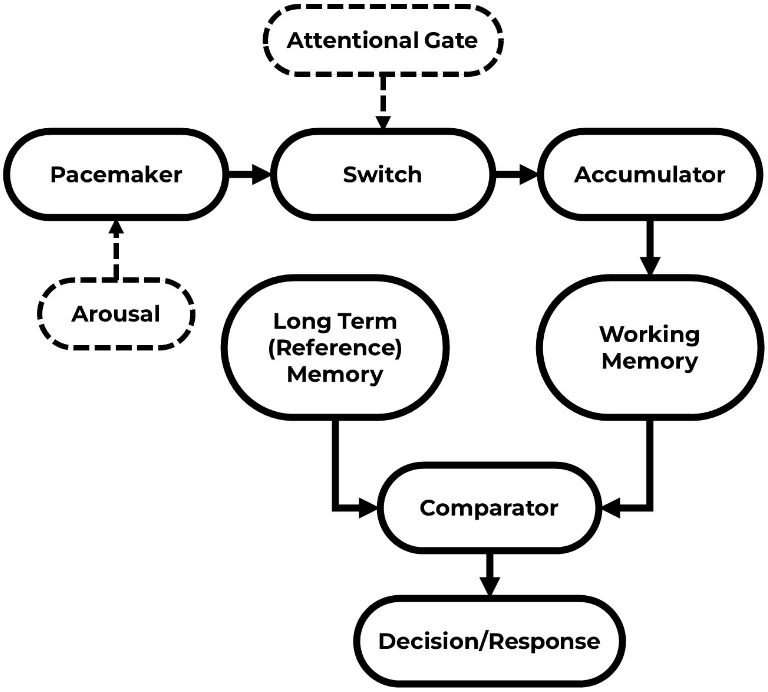


Figure 1.1. Illustration of the Pacemaker-Accumulator model components along with the attentional gate component.

Scalar expectancy theory

From its initial formulation, an influential variation of the PA model was developed in the 1980s based on investigations into animal behaviour during associative learning. The model, clearly based on the traditional conception of the PA model, begins with a Clock stage where the pacemaker emits pulses behaving like a Poisson timer, which although having some random variability, is relatively consistent. The flow of these pulses is controlled by a switch, that closes the circuit at the onset of the interval to allow the pulses to get through and opens again at the offset to stop the flow. Then, the pulses that got through are captured by the accumulator and stored in the working memory to be compared to a reference memory at the Memory stage. Finally, the Decision stage involves the comparison of the durations that will guide the perceptual judgment or behavioural response that ends up as the output of the whole process.

However, the key contribution of the model is not on the formulation of the model (which is close to the structure of the original PA model) but based on some key empirical findings from timing tasks. Gibbon et al. (Gibbon, 1971, 1977; Gibbon et al., 1984; Gibbon & Church, 1990) observed that animals learn to execute responses after a specific delay, indicating the capacity to operate with internal measures of elapsed time. Furthermore, they found that although responses peaked at the reinforced interval, the spread of these responses increased in proportion to the magnitude of the estimated duration. This property, known as the "scalar property of timing" became a key feature in timing research until this day, and served as the foundational basis of their model, the "Scalar Expectancy Theory" (SET) (named due to the scalar spread of responses at the expected time of reward).

The scalar property, crucial for understanding the consistency of time perception across different conditions, could be considered as a form of Weber's law for timing. It establishes a relationship between the variability of time estimates and the magnitude of the durations they represent. Generally, a linear increase in physical duration correlates with a linear increase in perceived duration, along with an approximately linear increase in the variability of these estimations (Buhusi & Meck, 2005; Gibbon, 1977; Grondin, 2010; Matell & Meck, 2000). This implies that sensory variance when measuring time intervals should be proportional to the magnitude of such intervals. Regarding where this variance would be generated, there is a disagreement about what component should be responsible for that, as while the original SET model proposes that it arises from noise in the comparison process, posterior variations like Killeen and Taylor's model (Killeen & Taylor, 2000) propose that it might be due to a noisy accumulator component.

To test this property across paradigms, modalities and species, a Weber fraction or a Coefficient of variation (CV) can be calculated as the ratio between estimate variance and physical duration $\left(\frac{\sigma^2}{t}\right)$. According to the scalar property, both the mean estimates and the standard deviation of these estimates should increase proportionally with the reference duration. Also, the Weber fraction or CV should remain constant across the different magnitudes of duration. Moreover, if the estimates are standardized by their reference durations, the distributions of these estimates should overlap (J. H. Wearden & Lejeune, 2008).

Attentional-Gate Model

In addition to the contribution of the SET, subsequent models also emerged to address additional aspects that could impact timing behaviour. The Attentional-Gate Model (AGM) proposed by Zakay and Block (Zakay & Block, 1997) introduced the significant role of attention in the timing process.

Based on the previous models, the rate of pulse generation in the AGM can be influenced by changes in arousal or attention. Similarly to Treisman's model, increased arousal leads to an accelerated pace of pulse generation. However, they also introduce an Attentional Gate component that moderates how the accumulator gathers the flow of pulses (see Figure 1.1 to illustrate the allocation of this component within the process). When more attention is allocated to tracking time, the gate opens wider, which allows for more pulses to reach the accumulator. Conversely, when attention is diverted from this task, such is the case of dual-task situations where the attention is at least partially shared with a different task, the gate narrows, and some pulses fail at reaching the accumulator. This provides a framework for understanding common experiences related to time like the common saying of "the watched pot never boils": when individuals focus heavily on the passage of time, their attention widens the gate, leading to more accumulated pulses and therefore longer perceived durations. In contrast, when attention is distracted by engaging activities like reading, watching a movie or having an interesting conversation, the gate narrows resulting in shorter perceived durations. Although these are anecdotical examples, the AGM help explain empirical findings about the effect of uncertainty, relevance, difficulty, or divided attention on timing tasks (Zakay, 2015; Zakay & Block, 1997).

To further elaborate on the role of attention in the timing process, Zakay also introduced the Temporal-Relevance Temporal-Uncertainty (TR–TU) model (Zakay, 2015). This model posits that the allocation of attentional resources for timing is not constant but dynamically influenced by the situational meaning extracted by the cognitive system. Temporal Relevance (TR) reflects how important temporal judgments are for adapting to a given situation, while Temporal Uncertainty (TU) indicates the amount of knowledge one has regarding the timing task. High TR automatically evokes a prospective duration judgment process and increases the allocation of attentional resources to timing. When TU is high, it indicates less certainty about the temporal aspects, thereby requiring more attentional resources to reduce this uncertainty. This interaction between TR and TU determines how situational factors dynamically influence the opening of the attentional gate and explains how attention and uncertainty jointly affect our perception of time.

Multiple-Oscillator Model

In parallel to the development of the different variations of internal clock models, a different set of models also emerged around the late 1980s from the recognition that biological rhythms play a crucial role in time perception and with a focus on finding some neurobiological substrate to support these processes. The Multiple-Oscillator Model (MOM) suggests that timing can be achieved through the interaction of multiple neural oscillators with different frequencies (Miall, 1989). These oscillators are reset at the onset of a timed interval and create distinct patterns of activity as time elapses due to their different asynchronous frequencies. At the end of the interval, the last pattern of the oscillators is used to interpret its duration (see Figure 1.2 for a visual example).

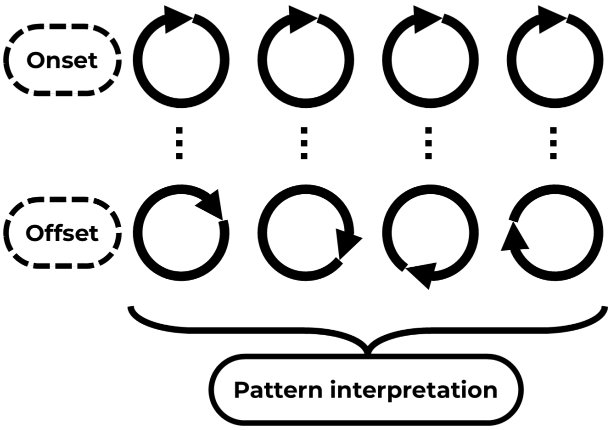


Figure 1.2. Example of the position of the multiple oscillators after a given time interval. The interpretation of the pattern of oscillation at the end of the interval determines the perceived duration.

Building upon this idea, Matell and Meck introduced the more neurobiologically detailed Striatal Beat Frequency (SBF) model (Matell & Meck, 2000, 2004;

Oprisan et al., 2022; Oprisan & Buhusi, 2011). It describes a distinction of roles in different areas, as oscillators are proposed to be located at the cortical level (particularly in the prefrontal cortex), but are also supposed to send signals to neural structures of the striatum of the basal ganglia to act as coincidence detectors, reading out the state of the cortical oscillators at the end of the interval. The unique activation patterns that are created at this point are what is finally used to encode the specific duration.

Duration-Channels Model

Another framework that integrates insights from multiple oscillator models and also originated apart from the internal clock models is the Duration-Channels model, which centres around a system of duration-selective neural structures (channels) that respond differently to specific durations (Heron et al., 2012). According to this model, the brain contains multiple clusters of neurons tuned to narrow ranges of preferred durations. This form of tuning to different ranges of stimulation magnitude is also present in other modalities, such as visual orientation, spatial frequency, or auditory pitch (Bruno & Cicchini, 2016; Heron et al., 2012). In the field of time perception, the preference of neuronal populations to specific durations has been already found in fMRI studies in animals and humans (Bruno & Cicchini, 2016; Hayashi et al., 2015).

To describe the perceptual process, when a stimulus is presented, it activates these channels to varying degrees depending on its duration and the preference of each channel. The pattern of activation across the channels is then interpreted by the brain to generate the mental representation of that duration (see Figure 1.3 for a visual example of these channels' activation).

Evidence for these models initially grounded on adaptation studies, where adapting to specific durations altered the perceived duration of subsequent stimuli (Heron et al., 2012), suggesting a saturation of said duration-channels. Moreover, neural imaging studies have revealed that duration-tuned cells in the auditory and visual cortex are engaged during timing tasks, indicating that temporal information processing relies on a distributed network of duration-selective neurons (Merchant & De Lafuente, 2014). This supports the idea that our perception of time is an emergent property of the activity within these duration-selective neural channels.

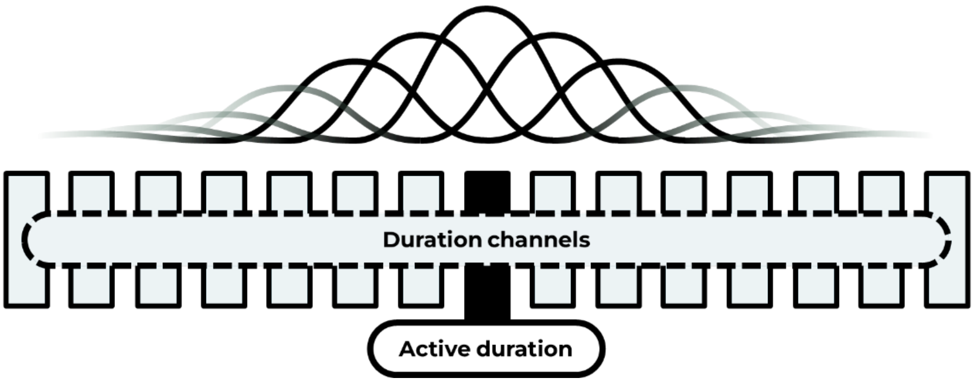


Figure 1.3. Illustration of the duration channels selectively activated by the active duration. The activation spreads through closer channels.

A Theory of Magnitude Model

Later, in the early 2000s, an alternative model less centred around a dedicated perceptual system of timing but more on a general magnitude system gained popularity. The Theory of Magnitude (ATOM) is a cognitive framework that proposes a common magnitude system for processing different types of stimulation, including time, space, and quantity (Bueti & Walsh, 2009; Choy & Cheung, 2017; Fabbri et al., 2012; Walsh, 2003). Instead of having dedicated systems for each type of magnitude, ATOM proposes that these mechanisms are shared and that this allows for the integration and comparison of different magnitudes more optimally in the brain, helping coordination across various domains. The theory is based on the idea that the brain represents magnitudes in an abstract way, independent of the modality or variable through which they are encoded. This abstraction is what allows perceptual mechanisms from other modalities to be borrowed for calculating and representing time. It also explains why time perception is so closely related to how we process space, and why we observe many parallel effects between space perception and time perception (Bratzke et al., 2023).

This was supported by behavioural and neuroimaging studies that provide evidence of brain regions involved similarly in the processing of time, space, and numerosity (Bueti & Walsh, 2009; Burgess et al., 2011; Cona et al., 2021; Parkinson et al., 2014; Skagerlund et al., 2016). However, there are also studies indicating some degree of independence, suggesting that although these domains share common mechanisms, they may not always follow the same computational properties (Sima & Sanayei, 2024).

Additionally, in relation to previous models, ATOM suggests that the internal clock system described in traditional models could be part of a broader magnitude system, that could be used to process other types of magnitudes as well. Due to the presence of Weber's law in many fields, the scalar property could also be a manifestation of a generalized magnitude property that affects not only time but also space and numerosity estimations similarly.

Drift-Diffusion Model

At the same time as Internal clock models were developing their variations, a broader group of models also emerged based on evidence accumulation. Originally developed to explain decision-making processes, the Drift-diffusion models (DDMs), originally developed by Roger Ratcliff (Ratcliff, 1978), proposed a way to describe how we reach perceptual decisions, especially when choosing between two alternatives. These models describe a process where noisy evidence is accumulated over time until this accumulation reaches either decision threshold, which terminates the evidence sampling and produces a decision that corresponds to that threshold (Balcı & Simen, 2016; Forstmann et al., 2016; Ratcliff, 1978; Ratcliff et al., 2016; Ratcliff & McKoon, 2008; Simen et al., 2011). Although this model was primarily focused on explaining reaction time distributions in two-choice tasks (without it being based on any specific modality), its principles were soon recognized as applicable to other cognitive domains, including time perception.

However, timing becomes a special case when describing the decisional process under DDMs which slightly differentiates it from other modalities. For example, if we are deciding the shape of a visual stimulus, this noisy accumulation of evidence is based on taking repetitive samples of what we are observing, but when it comes to observing a time interval, the same time we are using to sample the evidence is part itself of the stimuli. At the start of an interval, the evidence level begins at a neutral or zero value, and then gradually accumulates time as evidence. This magnitude of evidence can reach certain thresholds that determine judgments in duration comparison tasks or can also be translated into a quantitative value to respond in estimation tasks, which shows the relevance the establishment of thresholds has for explaining certain biases in decisional tasks.

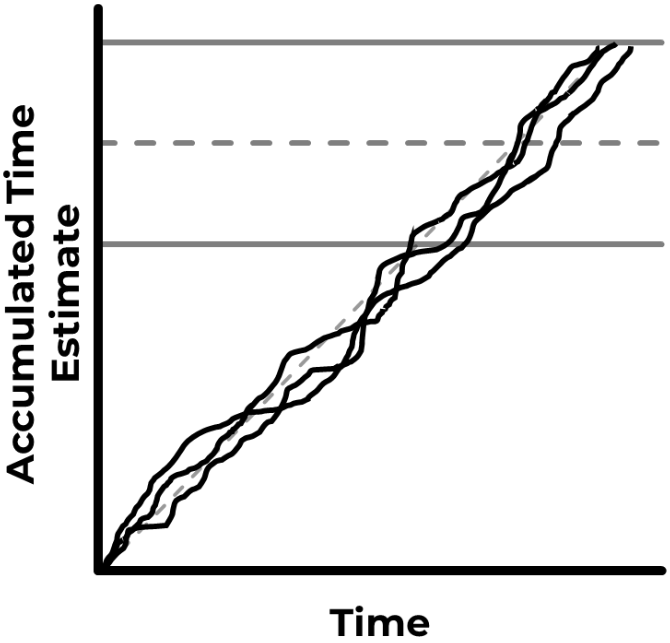


Figure 1.4. Example of the noisy accumulation through time. The grey diagonal dashed line represents how a perfect accumulation of estimated time would grow across time. The solid black lines show different instances of how the subjective accumulated time usually grows instead, with noise deviating the amount of perceived time from the actual elapsed time. The dashed horizontal line exemplifies a reference interval to be compared, and the solid horizontal lines represent the thresholds that determine the magnitudes at which the accumulated estimated time would be judged as longer or shorter than the reference time.

Although coming from different approaches, we can also find certain similarities between internal clock models and DDM, as the main components of these models could fulfil similar functions. On one hand, an important component of DDMs is the "drift", which refers to the rate of accumulation of evidence. If we focus on the estimation of time, this could be parallel to the rate of accumulation of pulses in an internal clock model, but in this case, instead of depending exclusively on internal factors, it can be determined by the quality of the evidence extracted from the stimulus or from memory. The second one, the "diffusion" component, represents random fluctuations during the accumulation of evidence, which is a form of noise that could be present at different steps of the process in an internal clock model and is critical to explain the high variability usually found in timing tasks.

Further variations of these models evolved to include many new factors, like variability in drift rates, starting points, nondecision times across trials, and non-static thresholds, and have been used to study various aspects of time perception, such as the effects of attention, memory and cognitive biases.

Bayesian Model

Finally, in a similar line to drift-diffusion models, we find another framework that emerged with a broader interest in understanding how the brain processes information and makes decisions under uncertainty, which ended up setting the ground for relevant models of time perception. We can trace it back to the 18th century with the formulation of Bayes' Theorem, which provided a mathematical framework for updating the probability of a hypothesis based on new evidence.

However, the application of this principle did not begin to generalize to cognitive science and perception until the late 20th century, when researchers applied it to explain that perception could be understood as a form of probabilistic inference, where the brain combines the initial belief or expectation about a particular state of the world (prior) with the probability of observing the sensory information (likelihood) to update their beliefs in a way that optimizes their estimates (posterior distribution) and help them interpret the world more easily (Gregory, 1980; Knill & Richards, 1996, 1996). Soon Bayesian models became a dominant framework in cognitive science and have since been used to explain a wide range of perceptual phenomena, from visual perception to motor control and decision-making.

This also arrived in the field of time perception, where they have also been particularly influential. Using the same principle, we could imagine an example where a person has a prior belief or experience that a familiar event usually lasts a specific amount of time, but then receives some noisy sensory information that suggests the event duration in this instance might be slightly different. In this case, we would predict that these two sources of information will be combined to produce a weighted average estimate based on their respective uncertainties that theoretically minimizes the probability of error (see Figure 1.5).

This approach contributed to understanding various phenomena in time perception, such as the central tendency effect, where people's time estimates are often biased towards the general average of the previously presented intervals (Acerbi et al., 2012; Jazayeri & Shadlen, 2010; Shi et al., 2013).

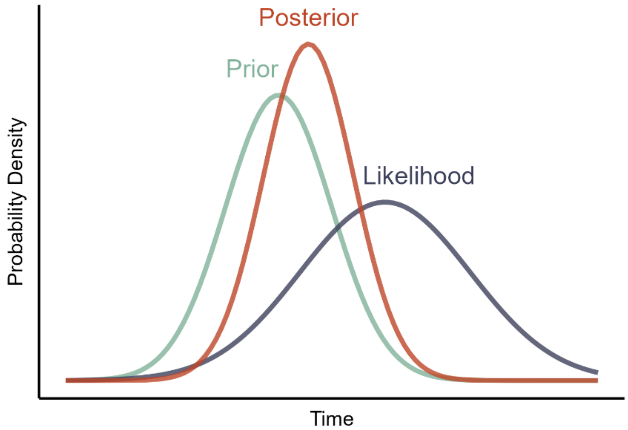


Figure 1.5. Bayesian process of time perception, where previous experience or expectations (prior) are combined with new sensory information (likelihood) to form an updated estimate of duration. The prior distribution reflects the initial belief or expectation about the duration of an event. The likelihood distribution is based on the new sensory evidence. The resulting posterior distribution is the updated estimate of the event's duration after integrating both the prior and the likelihood. It is centred between the prior and likelihood distributions, representing the brain's optimal estimate that minimizes uncertainty based on both sources of information.

This, for example, shows Bayesian models as part of the models that especially underscore the importance of uncertainty in the time perception process and give a reason for the prevalent variability of time estimates. If the brain estimates are probabilistic and inherently incorporate uncertainty, this will lead to variability in how a given interval is perceived and judged, as is often observed in experimental settings.

Also, an advantage of these models is that they are highly integrative and can be combined with elements from other time perception models. For example, the output of pacemaker-accumulators with noisy pulses could be considered noisy evidence that is later integrated probabilistically (Shi et al., 2013). Similarly, drift-diffusion processes could be accommodated too by framing the accumulation of temporal evidence as the process of updating probabilistic beliefs (Acerbi et al., 2012; Ratcliff, 1978; Simen et al., 2011).

MULTIPLE TIMING

These diverse models provide a robust framework for understanding how we perceive intervals of time. However, they often assume that intervals are processed in isolation, a scenario that rarely occurs in real-world settings. In reality, we frequently encounter multiple, even overlapping intervals that must be tracked and processed simultaneously. In such cases, the presence of simultaneous intervals in the mental space can interfere with the process. These intervals, whether they need to be tracked, maintained in working memory, or simply presented without any relevance to the task, can bias the construction of other time representations. Thus, these distortions of time perception are not caused by the intrinsic properties of the events but by the contextual demands of retaining multiple time intervals in the mental space, where they might compete and influence each other.

This is a common problem in real-life situations, where events are not isolated in time. When we are attending to a specific event, other events can often occur simultaneously in the same environment, and even the durations of events that are not currently active can retain relevance or influence our experience. For instance, while waiting at a traffic light, listening to music can affect how we perceive the waiting duration. The length of the song, its beat, and other properties can interfere with our experience of the waiting time. This concurrent or concomitant temporal information forms what we call the temporal context, and even when not actively attended to, it can leak into our perceptual process and interfere with our primary time-tracking activity. It includes any temporal information active in a given situation, such as the duration of events, the frequency of occurrences, or the synchrony between different elements, and even previously experienced temporal information stored in memory and integrated into the processing of our current surroundings also contributes to this context.

This introduces a level of complexity to our temporal processing that challenges some of the main models of timing and underscores how understanding the ways this temporal context can influence our time estimates becomes crucial for a comprehensive and generalizable theory of time perception.

Sequential events

To begin with, concurrent or successive events that are not successfully detached from the main event we are trying to measure are potential sources of perceptual noise that can effectively influence how we experience the duration of such events (Bryce & Bratzke, 2016; Jazayeri & Shadlen, 2010; Matthews & Meck, 2016). For example, when we are stopped at a traffic light, the waiting time may seem longer or shorter depending on the duration of other traffic lights changing within our field of view, even if these lights are irrelevant to us.

In this sense, studies focusing on the effects of preceding temporal information have shown that estimations can be affected by previously experienced durations. Hallez et al. (2019) found that reproductions of time intervals were influenced by previously experienced durations. Specifically, they found that reproductions tended to be overestimated when presented with an array of stimuli with longer durations and underestimated when the array consisted of shorter durations. This is suggested to be due to a compensation mechanism to face uncertainty, where participants relied more on their previous experience with that kind of stimuli, and therefore made their reproductions closer to that prior (Burr et al., 2013; Jazayeri & Shadlen, 2010). This mechanism aligns with the Bayesian theory of perceptual inference, which suggests that the brain integrates noisy sensory information with prior experiences to form a subjective perception of duration (Acerbi et al., 2012; Jazayeri & Shadlen, 2010).

In a similar line, studies on "carryover effects" in duration judgments reveal parallel results with the addition that not only previously presented durations but prior judgment can affect participant responses (Wehrman et al., 2020; Wiener et al., 2014). Interestingly, the direction of the effect differs between the two sources, where previous duration judgments typically lead to a central tendency effect, while previously presented durations often cause a repulsion effect, making current durations seem more distinct (Wehrman et al., 2020; Wiener et al., 2014).

Even irrelevant events can affect duration judgments. Burr et al. (2013) demonstrated that distractor intervals presented immediately before a target duration could bias judgments towards the distractor durations. Moreover, this effect persisted even when distractors immediately followed the target if both stimuli were presented in the same modality (visual, auditory or tactile). These findings demonstrate that not only the previous information influence the perception of posterior presentations, but also the events that are presented after it in the same temporal context can still have an effect (Burr et al., 2013). In such cases, the distractors could not affect the encoding of the target duration but would either interfere by modifying its representation in the working memory or by affecting the decisional stage. These findings support a Bayesian model that combines direct estimates of duration with a tendency to regularize intervals, suggesting that contextual effects involve both sensory processing and higher-level cognitive mechanisms.

Notably, when distractors are much longer than the target interval, their influence diminishes (Burr et al., 2013). This interaction can be explained by the channel-based model framework, where distractors activate duration-channels that interfere with channels associated with the target duration. This merging of activity from different channels would then deviate the outcome of the perceptual process by making the durations to be interpreted as more similar to the distractor durations.

This was also observed by Heron et al. (Heron et al., 2012), who used adaptation techniques to show how repeated presentations of a stimulus could shift the perceived duration of following stimuli. They found that after saturating a specific duration through many repetitions, right after presenting a target duration of the same or very close duration to the adapted one, the estimates of that duration were shifted away from the actual duration in a repulsive fashion. Based on the duration-channels framework, an explanation could be that if the channels were saturated, the strength of the signal close to those channels would be blocked or diminished, leading to a repulsive effect where close channels in the opposite direction would appear relatively stronger. Consistent with Burr et al. (Burr et al., 2013) findings, they also found that when adapted and test durations were different enough, the effect would fade, supporting the idea that the temporal proximity of durations plays a crucial role in the strength of perceptual distortions. In this case, the repulsive effects found (where perceived times are shifted away from the adapted durations) contrary to the assimilative effects mentioned earlier, could be explained by the saturation of the duration-selective channels. The paradigms that found assimilative effects should generate activation of those channels but not to the degree of generating saturation. Therefore, both types of effects could be explained according to this framework depending on what is happening at the channel level in response to the presented durations.

Altogether, these findings demonstrate that sequential events can deviate our timing processes, and from these both assimilative and repulsive effects can be expected depending on the paradigm and framework.

Simultaneous effects

So far, we have focused on serial timing effects from the presentation of duration information of previous or subsequent events. However, as mentioned before, the temporal context also includes information about the temporal properties of simultaneous or overlapped events. This aspect of temporal context is addressed by the "Multiple Timing" framework described by Brown and West (1990). According to their initial definition, Multiple Timing involves the capacity to attend and extract duration information from multiple sources simultaneously. Here, this framework aims to understand how simultaneous intervals are processed, and how their overlapping can influence duration estimation.

Now when we talk about simultaneous intervals, we refer to those that occur fully or partially at the same time. Whether one is fully embedded within the other or their onsets are just shifted from one another, there is at least some time during which both intervals are active. Many real-life situations present this kind of setting, and sometimes we need to keep track of multiple of these intervals at once. For instance, in basketball, players and referees must keep track of several overlapping intervals; they must track simultaneously the 24 seconds interval they have to attempt a shot, cannot stay in the are under the basket for more than three seconds and must inbound the ball before five seconds run while the ball is out of bounds of the playing area, all at the same time. Similarly, healthcare professionals often monitor the administration times of medications for multiple patients, which requires precise tracking to ensure timely delivery. And in a longer timescale, project managers also have to oversee different tasks and sub-projects progressing concurrently, each with its own timeline. All of these are just a few examples of many situations in which our ability to track multiple overlapped intervals is key to our success.

From a more theoretical perspective, this ability challenges some of the most traditional timing models, which typically focus on tracking a single event or sequence. Unlike sequential timing, when multiple streams of time need to be tracked concurrently, many of these models fall short of explaining fully the process of timing. This raises the still unanswered question of whether we are actually able to track multiple intervals independently or else we depend on some strategies for exploiting the mechanisms we already have from sequential timing to solve these tasks.

Although scarce, some studies addressed the issue of simultaneous multiple timing. For example, Kawahara and Yotsumoto (2020) studied the effect of simultaneous distractors on duration reproductions. They found that when a target interval was presented along with distractors of longer durations, reproductions tended to show a positive error (overestimation), and the opposite happened when distractors had shorter durations than the target interval. This finding aligns with the assimilative effects found in sequential presentations, where an averaging effect occurs between the target duration and the durations of other elements in the temporal context (Ayhan et al., 2012; De Corte & Matell, 2016; de Montalembert & Mamassian, 2012). In a similar line, De Corte and Matell (2016) investigated interval timing and temporal averaging in rats. They found that when rats were presented with two temporal cues, each signalling a different reward interval, they behaved as if they computed a weighted average of the durations. This "temporal averaging", that could be understood within the context of Bayesian Decision Theory, suggests that the brain integrates multiple sources of temporal information based on their reliability. However, when comparing the effects of simultaneous presentations with sequential or individual presentations, the most common findings are that performance in duration discrimination is worse than compared to sequential tasks (de Montalembert & Mamassian, 2012), and degrades as the number of simultaneous elements increases (Ayhan et al., 2012) or when overlapping distractors are presented (Morgan et al., 2008). Altogether, these results support the idea that timing simultaneous durations involves higher cognitive demands and increases perceptual noise in the process.

As previously noted, traditional timing models were primarily designed to explain the mechanisms underlying the tracking of single intervals, but they might struggle to explain the cognitive processes involved when multiple intervals must be monitored simultaneously. However, researchers have developed variations and extensions of these classic models to address the complexities of simultaneous multiple timing.

For example, pacemaker-accumulator models are traditionally built with individual intervals in mind, as they consist of a single pacemaker and a single accumulator that, although working for simple, non-overlapping intervals, would have trouble when having to keep the count of pulses from two different events. However, alternative versions of these models have been proposed to approach this issue. For instance, Matthews (2013) proposed an alternative approach, suggesting that we do not track overlapping events separately but rather as segments of a sequence. His research showed that sequences with equal duration segments were consistently judged as longer than those with varying segment durations. Additionally, they found an interaction between the decelerating or accelerating structure of the segments and the overall duration of the sequence, where short sequences were judged as longer when sequences were accelerating whereas longer accelerating sequences were judged as shorter. This highlights an effect of recency, that they described as a differential weighing of the contribution of each segment to the overall duration. According to their theory, the Weighted Sum of Segments, the more recent segments (those closer to the offset of the overall sequence) are weighted more heavily in the final judgment of the overall duration, similar to a fading memory trace. This model suggests that interval sequences are perceived as distinct segments timed individually and then summed to estimate the total duration, with each segment's contribution weighted by its recency. In their study, the long interval was divided into three segments: before the short interval, during the overlap, and after the short interval. This approach allows a single accumulator to manage overlapping intervals by treating them as sequential segments stored in memory and summed accordingly.

Bridging this theory with simultaneous multiple timing, we could imagine that one way of measuring simultaneous intervals could be to keep track of the different segments generated by the intersection of both events and then to sum the duration of those segments where each of the events was present.

Alternatively, the Single Pacemaker Multiple Accumulator (SPMA) model offers a different perspective. Proposed by van Rijn and Taatgen (2008), this model suggests that a single pacemaker emits pulses for all intervals, which are counted by multiple accumulators, each dedicated to timing a different interval. This approach also accounts for the scalar property of timing by proposing that pulse generation is nonlinear, with pulse intervals increasing over time. With this model, tracking the duration of overlapping events would be possible due to the dedicated accumulators. However, the SPMA model faces challenges such as dual-task costs, where sharing attention between multiple intervals results in slower accumulation of pulses and increased variability or inaccuracy in timing.

To compare these two possibilities, Bryce and Bratzke (2016) tested both models to see which one could explain the effects of overlapping intervals better in a reproduction task. In their study, participants were asked to reproduce the duration of two nested intervals presented as visual stimuli, where one was fully embedded in time within the other. The onset of the short interval (1 s) had a delay with respect to the onset of the long interval (3 s) by varying amounts (250 to 1750 milliseconds), creating different degrees of overlap. Their results showed that the reproduction of the long interval decreased as the short interval appeared later within it, while the short intervals were unaffected by their temporal position within the long interval. Although these findings could be similarly predicted by an adapted version of the SPMA model where dual-task costs impact only the long interval, they were even better aligned with the recency effects expected from a “the SPSAweighted” model with one pacemaker and one accumulator where only the timing of the embedding interval required summing of segments. Additionally, participants' responses for reproducing the short interval were delayed when there was more time between the end of the short and long intervals, suggesting they replayed the entire sequence, which supports the notion that participants treated both intervals as part of a single sequence rather than independently and provide a plausible explanation of how the estimation of overlapped intervals is produced.

The aforementioned approaches provide theoretical frameworks to explain how simultaneous multiple timing could be accommodated within most classical models, although similar adaptations can be made too with more recent models from different frameworks. In summary, understanding the mechanisms through which overlapping durations influence time perception is a challenging endeavour that is crucial for developing a comprehensive theory that accounts for real-world situations where multiple time intervals must be tracked concurrently. To that aim, the present thesis will address simultaneous multiple timing tasks at different levels of complexity with a focus on developing novel models that can contribute to a better understanding of how humans process and manage multiple time intervals simultaneously.

UNCERTAINTY IN TIME PERCEPTION

As seen through this general introduction, we find that the diverse timing models that try to illustrate the intricate process of how we perceive and measure time underscore a common theme: the inherent uncertainty in our time estimations or temporal judgments, which seems to be even amplified when managing multiple overlapping intervals. Because of this complexity, using precise methods to measure and understand the variability and reliability of our temporal judgments is essential for both theoretical and practical applications.

In this section, we will delve into the various approaches developed to measure uncertainty in time perception, highlighting both their advantages and the limitations they must face.

Variability of estimates

From the different ways of approaching the measurement of uncertainty in time perception, probably the most common or simple approach is by calculating the variability of estimates in quantitative tasks. For example, participants deliver a quantitative response by generating a physical interval in production or reproduction tasks or by labelling the duration with a quantity in estimation tasks that represents how long they perceive a given interval is. If these estimates are more variable, we could infer that there is probably a greater degree of uncertainty (see Figure 1.6). However, this variability could be caused not only by uncertainty in the mental representation of the interval but also by other sources of response noise such as motor components.

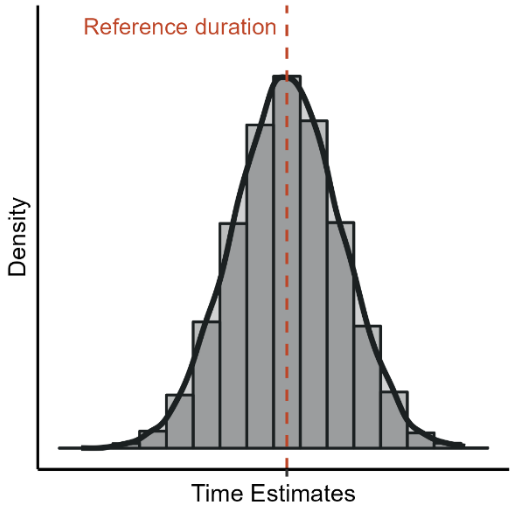


Figure 1.6. Illustration of the variability of time estimates around a reference duration (dashed red line). The spread of the estimates around the reference duration can be used as the measure of uncertainty in the participant's perception of the reference duration with a broader distribution suggesting higher uncertainty.

Slope of the psychometric function

Parallel to the variability measure in quantitative tasks, we could also calculate a psychometric function in a duration discrimination or bisection task and obtain a slope or sensitivity measure. A steeper slope would suggest a very clear mental representation of that interval (therefore less uncertainty). See Figure 1.7 for an example of how this would be reflected in the results of a temporal judgment task.

The problem with these options is that the uncertainty measure that we obtain is not specific to an individual response but refers more to the global performance during the task. If we can only obtain a measure of how clear the mental representation is for the whole task, it can be hard to investigate how uncertainty fluctuates throughout the different trials or manipulations during the same block.

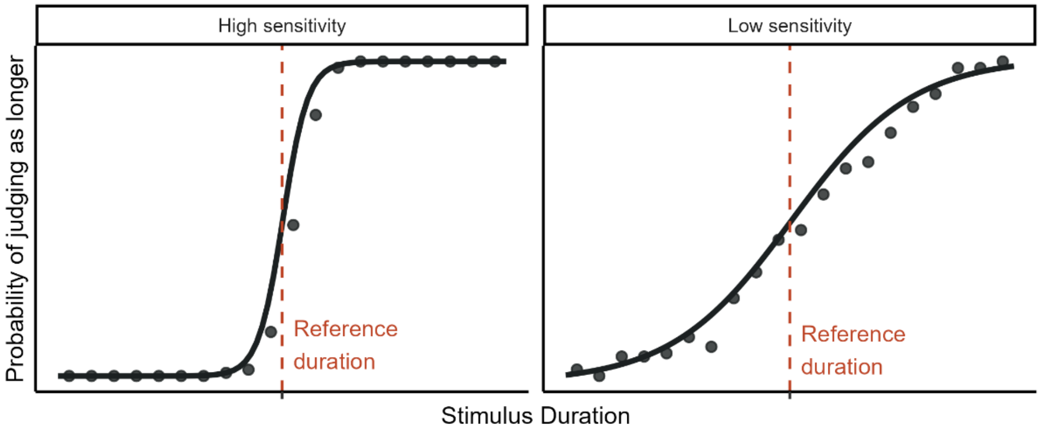


Figure 1.7. Example of the psychometric function obtained in a duration judgment task. The left example depicts high sensitivity, where the steep slope indicates a clear distinction between different durations and therefore lower uncertainty. In contrast, the plot on the right shows low sensitivity, where the flatter slope suggests a more gradual transition between judgments, reflecting greater uncertainty in temporal judgments of close durations.

Confidence judgments

A common alternative to these approaches that delivers a measure on a single-trial basis is to integrate confidence judgments into timing tasks to address the interplay between performance variability and metacognitive assessments of uncertainty. For example, Lamotte et al. (2017) combined a temporal generalization task followed by a confidence judgment, where participants learned the standard duration of an auditory stimuli, and then had to judge whether the following stimuli had the same or different durations. After each duration judgment, participants were asked to make a confidence rating on a scale from 0 to 100 regarding how sure they were of their answer. Their results revealed that confidence aligns with the accuracy of duration estimates, especially when those durations closely match a standard interval. This suggests that confidence judgments can reflect the uncertainty inherent in temporal discrimination tasks. Similarly, Akdoğan & Balcı (2017) used a duration reproduction task followed by error monitoring judgments, illustrating that participants can introspectively assess the accuracy and direction of their timing errors, linking error awareness to confidence levels.

Second-order judgments

Following a similar approach but taking a step further, Cropper et al. (2024) and Corcoran et al. (2018) employed modified temporal-bisection tasks to measure second-order confidence judgments over multiple first-order estimates. In these tasks, participants made two interval estimates per trial and then were asked to identify which one was more accurate, assessing both time perception and confidence of multiple estimations. Lastly, Jovanovic et al. (2023) investigated the effects of dopamine depletion on timing and confidence, demonstrating that neurochemical changes can influence both the accuracy of timing tasks and the confidence in those tasks.

Overall, these studies found proficiency in making metacognitive evaluations of temporal judgment accuracy, and that adding confidence judgments to timing tasks offers a valuable method for accessing the uncertainty in perceptual decisions through the lens of metacognitive confidence. However, the integration of explicit judgments requires participants to be aware that their confidence is being measured, potentially influencing their responses. This awareness could inadvertently affect the very judgments that are being studied. Furthermore, these methods lengthen the task by requesting an additional response after each trial, which increases the overall duration of timing experiments potentially impacting participants' fatigue and engagement in the task. It also requires the implication of higher cognitive functions, as participants must engage in the evaluation of their own performance, which can be susceptible to biases and external interferences that might not be directly related to the uncertainty being measured.

Peak-interval procedure

Departing from the metacognitive assessment approach, other methods have been developed closer to the original measure based on the variability of estimates. In this line, the Peak-Interval (PI) procedure allows the obtention of an uncertainty measure on a single-trial basis without requiring additional responses. In this protocol, participants (typically non-human animals) are trained on a fixed-interval reinforcement schedule, where actions such as pressing a lever are rewarded after a predetermined period. After learning the reinforcement time, probe trials are presented without reinforcement, where subjects generate multiple responses as if they were expecting the reward at the usual time (Catania, 1970; S. Roberts, 1981). These responses become more frequent as the elapsed time gets closer to the reinforcement time, where the response rate usually peaks (see Figure 1.8 for an example of this behaviour). Here, we can obtain the distribution of response rates across time, and the spread of these response rates provides a potential measure of uncertainty regarding how close participants feel their responses are to the reinforced interval. Studies supporting the scalar expectancy theory have demonstrated that this variability in response rate is proportional to the length of the interval, which suggests a direct relation between response rate dispersion and uncertainty (Gibbon & Church, 1990; Rakitin et al., 1998).

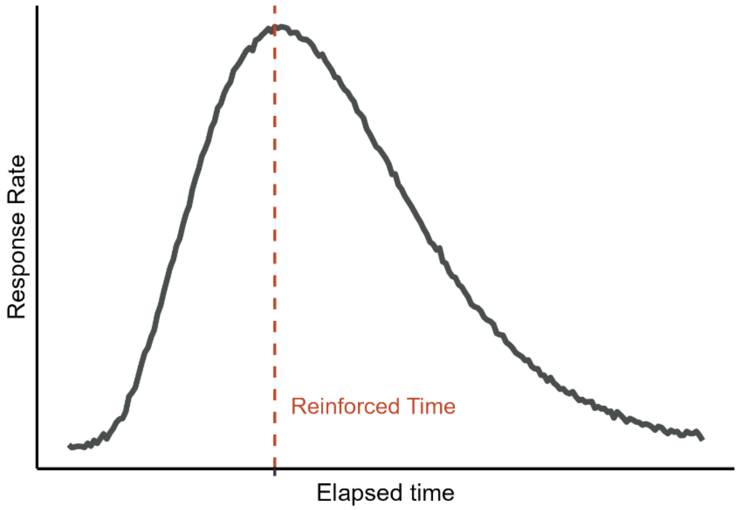


Figure 1.8. Example of the response rate variating across time in a Peak Interval procedure. The response rate increases as the time approaches the reinforced interval, marked by the vertical dashed red line, peaks around this time, and decreases gradually. Uncertainty can be measured by the spread of the distribution around the reinforced time.

However, despite the advantage that the response rate is a measure obtained at each trial and does not require any additional metacognitive queries, the requirement for extensive training and a consistent reward system makes the PI procedure a more complicated option for broader applications across different species and experimental paradigms. The need for multiple responses in each trial and the difficulty of modifying this protocol for different settings makes us keep looking for an even better option.

Range values

A different approach that focuses more on obtaining a measure of uncertainty than extracting it from estimated values is by asking for a self-determined range in the perceived magnitude of a stimulus. This approach, which has been explored in different perceptual domains, consists of asking for a range of minimum and maximum values within which the perceived magnitude might fall.

For example, Graf et al. (2005) used this method to assess humans' uncertainty when extrapolating motion trajectories. In their study, participants were presented with moving objects that followed a random walk, and after a brief occlusion, they were asked to define a "capture region" where they predicted the object would be. The width of this region was then expected to align with their uncertainty about the location of the object, with greater areas associated with more uncertainty. Similarly, Honig et al. (2020) used a colour wheel to obtain a measure of uncertainty in the memory of a previously presented colour. They asked participants to draw an arc around the colour wheel that included those colours that they believed represented the one they were presented. Here, the width of the arc served as a metric for uncertainty, and its length was considered to indicate participants' confidence in recalling the colour.

As for the interest of the present thesis, this approach has also been used in time perception. Grondin and colleagues (Bisson & Grondin, 2013; Grondin & Plourde, 2007; Tobin et al., 2010; Tobin & Grondin, 2012) used verbal estimation tasks to ask participants for maximum and minimum retrospective estimates about the duration of different activities. In addition to giving an estimate of how long they believed the duration lasted, they also had to deliver a minimum value that they thought could also represent the duration they experienced and a maximum value. Here the expectation of noise or error in the estimation becomes explicit, and participants are able to delimit the range they expect this noise to reach, obtaining a measure of uncertainty with the distance between minimum and maximum values. However, this simple yet clever way of obtaining a range that captures the inherent variability of human estimations could still be affected by similar biases as confidence judgments, since participants have to retrospectively ponder what range they want to determine.

Start-stop procedure

Finally, we find an approach that combines quantitative measures such as reproduction tasks with the possibility of obtaining an equivalent to the sensitivity of difference limen on a single-trial basis. The start-strop procedure, introduced by Kladopoulos et al. (1998), consists of instructing participants to produce a duration estimate by bracketing the endpoint of the interval with a range rather than a discrete value (as we would find, for example, in a conventional reproduction task). Participants are asked to mark the end of the target interval by starting the response behaviour right before the duration would elapse and releasing it once it had already elapsed. This creates a bracket around the point equivalent to a traditional reproduction estimate. Also, participants are encouraged to encompass the ending time of the target duration within these two moments, so they should be performing this continuous response when the duration finally elapses, but still trying to leave the shortest time possible between the starting and end of the behaviour.

Kladopoulos et al. (1998) proposed that these two latencies, defined as start and stop times, and the interval between them would allow for the estimation of a parallel measure of the point of subjective equality (PSE) and the difference limen (DL) obtained in a psychophysical task but on a single-trial basis. In this case, the PSE and the DL would depend on the allocation and length of the bracket respectively. Most importantly, the DL serves a role similar to the standard deviation of temporal estimates in a traditional reproduction task, or the slope of a psychometric function, which makes it a potential candidate for indicating the level of uncertainty.

This procedure has the advantage that, in contrast to some of the methods mentioned above, we can obtain a duration estimate and a potential measure of the uncertainty associated with it both on each individual trial, rather than inferring them from response distributions. Also, as these measures are all part of the behavioural response that represents the estimate and do not depend on a retrospective metacognitive evaluation, it leaves fewer opportunities for decisional biases to interfere.

As a more recent example of this approach, Balcı et al. (Balcı et al., 2013) studied the influence of dopamine on the connection between reward processing and time perception by measuring the time at which mice entered a platform in anticipation of a reward and left after the expected reward delivery time. Similarly to the start-stop procedure, they also obtained start and stop times, with the entry and departure times from the platform. Their findings indicated that larger reward sizes led to earlier response initiations, thereby increasing both the width of the start-stop interval and the variability of estimates, highlighting not only a relation between these timing measures with reward magnitude, but more importantly for our subject, a relation between the width of start-stop times, the supposed measure of uncertainty, and the coefficient of variation of the time estimates, pointing out the spread of start-stop intervals as a good candidate for a measure of uncertainty.

However, despite the highlighted advantages and the potential of this method, it appears that this approach has not been explored to its full potential. Also, no direct comparison has yet been made to assess its capabilities for measuring uncertainty against other approaches.

Disadvantages

In general, although the relevance of measuring uncertainty is clear, there is no method free of disadvantages. As mentioned, solutions like measuring the variability of estimates in a quantitative task (production, reproduction, or verbal estimation), obtaining the psychometric function, or using second-order judgments all have in common that the approximation to a measure of uncertainty is a global value for all the task or block, but does not describe the uncertainty associated to each individual response. For this reason, although informative, it can be hard to assess the effects of fine manipulations in the task in a non-blocked design.

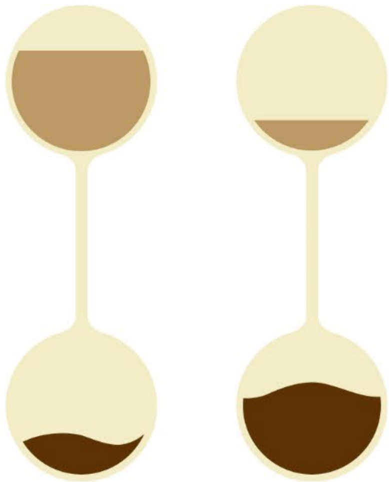
Other solutions, like asking for confidence judgments, calculating the spread of response rates in a peak-interval task, obtaining maximum and minimum verbal estimates, or measuring the spread in a start-stop procedure do not imply this issue, as they provide measures on each trial. This makes them more reliable for studying how uncertainty may vary from changes in the properties of the stimuli on a trial-by-trial basis, or even to see how uncertainty may fluctuate throughout a task. For instance, in adaptive learning environments where the feedback given on each trial is used to adjust subsequent responses, having a trial-specific measure of uncertainty can help identify how well a participant is integrating new information and adjusting their time estimates. Additionally, in clinical settings, where patients might exhibit variability in cognitive performance due to fluctuating attention levels or neurological conditions, trial-by-trial measures can provide more granular insights into their perceptual stability and the effectiveness of interventions over time.

Another point to keep in mind is that some of these measures rely on metacognitive capacity, which can obscure what we are truly trying to assess. Confidence judgments or second-order judgments, for example, may not be ideal for measuring a more basic and not necessarily conscious form of uncertainty. The concern is that these metacognitive measures can be influenced by factors that arise after the initial uncertainty of the estimation itself, such as a participant's self-awareness, confidence levels, or decision-making strategies. These post-estimation factors can mask the true level of uncertainty associated with the initial time perception, thereby complicating the interpretation of the results.

Finally, another common and problematic issue in time perception tasks, often overlooked by the general public but well-known to timing researchers, is that these tasks can easily become quite boring and unengaging for participants. While this may seem like a minor issue in other fields, the monotonous and lengthy nature of timing tasks can lead to a lack of motivation and attention in participants, which in turn can interfere with their time estimates. Attention plays a crucial role in these processes, making it critically important to keep participants engaged to ensure reliable measures.

However, many of the solutions proposed above risk making already lengthy tasks even longer. Asking for confidence judgments or second-order judgments adds additional questions, disrupting the task flow and nearly doubling the task time. Similarly, measuring the spread of reproduction times or obtaining a psychometric function requires many repetitions to achieve a reliable measure of variability. Therefore, when considering an ideal measure of uncertainty in time perception, we should aim for approaches that provide good reliability with shorter application times.

For this reason, one of the objectives of the present thesis will be to propose a potential solution to this problem, contributing to the evolving methodology of time perception research. By developing a more engaging and efficient approach, this work aims to enhance the informative value of participants' responses, ultimately advancing our understanding of temporal cognition.



Part II

RESEARCH OBJECTIVES AND HYPOTHESES

RESEARCH OBJECTIVES

In the general introduction, we discussed the fundamental nature of time perception, highlighting its critical role in various cognitive processes and everyday activities. We examined several key models that have been proposed to explain how humans perceive and measure time, from the early internal clock models to some of the most recent and varied models. Each of these models offers unique insights into the mechanisms of time perception, yet they often assume that time intervals are processed in isolation, which is rarely the case in real-world scenarios.

We then introduced the concept of multiple timing, emphasizing its relevance as a less explored but significant aspect of time perception, that is crucial in real-world situations where temporal information from different sources must be integrated and maintained, such as monitoring traffic lights while driving or managing various tasks in a fast-paced work environment. We reviewed how simultaneous timing tasks often result in significant performance impairments, with high variability in participants' estimates due to the interference from the perceptual noise increase by having to manage multiple temporal inputs. However, the results in this area are inconclusive, especially regarding sequential events, where opposite effects can be found, and simultaneous effects where there is still limited research. One of the major challenges in studying the human capacity for measuring simultaneous durations is the high level of variability in participants' performance and the difficulty in accurately identifying and quantifying the sources of noise associated with it.

To address these gaps, we propose two studies on multiple timing situations with increasing levels of complexity. The first study involves a simple perceptual judgment task assessing the effect of simultaneous overlapping durations. The second study involves a more complex task evaluating the capacity to adapt behaviours to find an optimal pattern under uncertainty, guided only by the knowledge of event durations and the ability to track and frequently update the elapsed time.

Additionally, we emphasized the critical role of uncertainty in understanding the timing process in noisy environments. Uncertainty refers to the variability or unreliability in participants' time estimates, influenced by internal cognitive processes and external contextual factors. Accurately measuring and quantifying this uncertainty is essential for a deeper understanding of how individuals perceive time and how their mental representations of duration are formed and influenced by various factors. Most traditional approaches to measure this uncertainty have notable limitations. Addressing this matter in our third study, we test an alternative method designed to overcome some of these disadvantages, involving a slight modification of the traditional reproduction task that allows for a more direct measurement of the uncertainty associated with each estimate on a single-trial basis.

With this, the overarching aim of the present thesis is to deepen our understanding of time perception by exploring the mechanisms underlying multiple timing and developing innovative methods to measure uncertainty. This research seeks to fill critical gaps in the literature and provide practical tools for future studies in cognitive psychology.

This general goal can be broken down within each study into the following specific objectives:

The first three objectives will be covered by a study where we investigate how presenting simultaneous distractors with varying durations affects the perceived duration of an attended event. We adapted a common size-illusion to the temporal modality to assess how participants' duration judgments were affected by the durations of irrelevant stimuli present in the environment. Through this experimental design, we aimed to explore how multiple timing can act as an interference to targeted timing processes in a simple setting. Moreover, we developed a computation model to explain and predict the interference between attended and unattended events.

Objective 1: Investigate the Influence of Simultaneous Distractors on Perceived Duration

The starting focus of the thesis is to directly explore how the temporal properties of simultaneous events, in this case, their duration, can influence the perceived duration of a target event. We will evaluate any systematic shifts in the duration judgments of target stimuli that might vary in relation to the duration of the concurrent distractors. By using methods from psychophysics, we expect to capture any interaction between distractor and perceived target durations.

Objective 2: Compare whether the type of effects found in the size illusion remains the same when translating it to the time domain.

According to generalized magnitude system models, time mechanisms often follow the same principles as size or numerosity domains. We intend to test this relation by directly translating a consolidated size illusion to the temporal domain to check whether the interferences manifest in the same way between domains. This will help us understand the interplay between different perceptual systems, and how generalizable interference effects can be.

Objective 3: Provide a computational model that helps explain and predict the perceived duration of an attended event based on its difference from distractors' durations.

To provide a quantifiable way of predicting interference effects from simultaneous multiple timing, we will define a computation model that describes how the duration of simultaneous distractors can be integrated into the processing of the target stimulus' perceived duration. This will contribute to timing research by facilitating the prediction of multiple timing effects as well as providing a theoretically grounded model that also explains why this interaction takes place.

The next three objectives will be addressed by a second study that will focus on a more active use of multiple timing processes and explore how participants adapt their monitoring patterns to unpredictable events based on the information extracted from the temporal structure of the environment. We designed a task that simulates a driving environment where participants had to adjust their behaviours based on time variables that were taking place simultaneously. In order to succeed in the task, participants would have to successfully extract, maintain and work with several timing properties of the simulation, and then apply them optimally to guide their behaviour. We also developed a computational model of an optimal observer to assess participants' performance and optimal selection of monitoring strategies.

Objective 4: Develop a task to measure observers' monitoring patterns in response to unpredictable temporal events.

To provide a more comprehensive view of multiple timing, we will develop a task where participants' success depends on their capacity to measure and work with multiple time estimates at once. Additionally, in contrast to previous tasks, we will also focus on presenting this task as a simulation of a real-life situation to promote participants' immersion and generalizability to real-world phenomena.

Objective 5: Assess participants' optimal selection and adaptation of monitoring patterns according to the temporal structure of the environment.

Based on this task, we will test out participants' flexibility to adapt to changes in the temporal dynamics of the environment. We will assess the optimality of their behaviours to explore which temporal aspects of the task they are able to capture and adapt to. This will allow us to compare the integration of changes in temporal structure that are caused by internal factors, such as motor limitations, or by external factors, such as the duration of external events. It will finally help us ascertain to what extent humans can exploit the use of multiple timing to succeed in complex tasks.

Objective 6: Develop a model predicting participants' capacity to detect unpredictable temporal events based on their integration of temporal features.

Along with the previous objective, we will also develop a computational model to describe how the different elements of the temporal structure of this complex task are integrated into an optimal behaviour selection. This will allow us to predict participants' performance based on their behaviour, as well as assess the optimality of their behaviour.

Finally, the last three objectives will turn the focus from multiple timing to the relevance of uncertainty in time perception. To address this, our third study tests a modified reproduction task as a potential way of measuring uncertainty in time estimations. Participants' estimates were obtained and compared using both the traditional reproduction task and the modified version to ensure that reproduction methods are equivalent. Then, the proposed measure of uncertainty will be compared with conventional approaches. Additionally, we will assess the potential advantages of this new method to investigate the nature of noise contributions to time estimation.

Objective 7: Compare the traditional reproduction method of time estimation with an alternative version, the Bracket method of reproduction.

To make sure that this modified task does not interfere with participants' performance or bias their estimates in relation to the traditional method, we will test the equivalence of the time estimates obtained with each approach. This validation is key to assessing the method as a valid alternative to the traditional method and thus allows the evaluation of the following objectives.

Objective 8: Assess the Bracket method's capacity for measuring uncertainty.

The main objective of this last segment is to provide a novel measure of uncertainty in quantitative time estimates. To this aim, we will assess the additional metrics obtained from this method as a viable measure of uncertainty. These measures should be representative of the uncertainty obtained from other traditional approaches.

Objective 9: Investigate the nature of noise contribution to uncertainty in time estimates through the Bracket method.

We will also explore the potential of this method as an alternative way to investigate the nature of noise in this type of task. The new metrics provided by the task, in addition to allowing for an uncertainty measure, could also explain how the noise associated with this uncertainty evolves across different levels of stimulation. This is a very critical topic in time perception research since it contributes to the discussion regarding the scalar property of timing.

HYPOTHESES

Based on the preexisting results about simultaneous multiple timing and the specific objectives we defined, the following hypotheses are formulated:

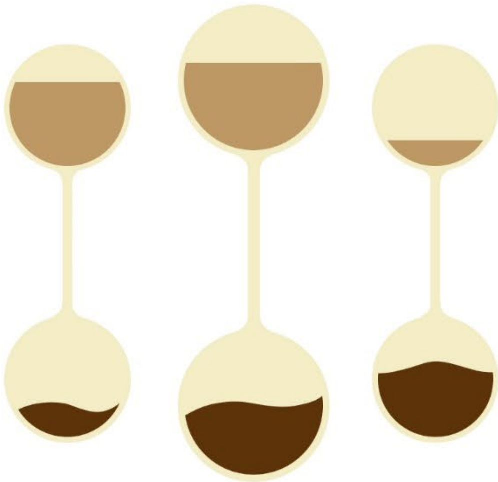
Simultaneous Multiple Timing effects: Although inconclusive in general multiple timing, in simultaneous multiple timing tasks where overlapping intervals are presented as distractors or are not the target of our estimations, the presence of these interfering stimuli produces in some cases effects of averaging or central tendency. Because of this, we expect to find this type of effect on judged durations when presenting overlapped intervals of different durations.

However, if the mechanisms of size and time perception are shared, as proposed by models such as the ATOM model, by adapting a size illusion that produces a contrastive effect we would expect to find also a repulsive effect when adapting the paradigm to the temporal domain.

The finding of either a positive or a negative effect would highlight which theory describes more accurately distortions in multiple timing.

Active use of Multiple Timing: Due to the temporal complexity of many real-life situations, we believe that leveraging the capacity of measuring, holding and working with multiple time representations to solve a complex task can be possible. We expect that humans are able to optimally measure and integrate into their behaviour multiple properties of the temporal structure of a dynamic environment.

Measurement of Uncertainty: Based on pre-existing methodological ideas, we expect that the method we propose for measuring uncertainty will overcome the main caveats from traditional methods. First, we anticipate the estimates obtained from the modified and the traditional methods to be equivalent. Then, we expect the measures obtained with this method to correlate with traditional methods, validating it as an alternative for measuring uncertainty in quantitative timing tasks. Specifically, we expect the bracket measure obtained on a single-trial basis to be equivalent to the variability of multiple time estimates, as well as to variate accordingly to timing principles that are key for understanding uncertainty, such as the scalar property of timing.



Part III

STUDY 1:

THE EFFECT OF SIMULTANEOUS DISTRACTORS ON INTERVAL TIMING

ABSTRACT

When assessing the duration of an event, our perception is often influenced by concurrent external stimuli. In everyday life, events rarely occur in isolation; they overlap, creating a complex temporal context. Research on multiple timing suggests that this overlap can lead to a central tendency effect, where perceived durations are biased towards the average duration of simultaneous stimuli. However, in some cases, these concurrent events can cause a repulsion effect, shifting perceived durations away from the overlapping stimuli.

Our study investigates this phenomenon by examining how the duration of simultaneous distractors affects the perceived duration of a target event. Using a novel perceptual decision task, we found that most participants experienced a central tendency effect, while a few exhibited a repulsion effect.

To explain these results, we developed a computational model based on the duration-channels theory, incorporating a leaking factor to account for the interference the distractors' durations produce in relation to how similar they are to the target.

Our findings highlight individual differences in susceptibility to distractor influence, which are linked to task uncertainty and perceptual noise tolerance. This research provides insights into how temporal context affects duration perception, offering a foundation for understanding the cognitive processes underlying multiple timing.

Published as:

Boned, J., & López-Moliner, J. (2022). Duration judgments are mediated by the similarity with the temporal context. Scientific Reports, 12(1), 22575. https://doi.org/10.1038/s41598-022-27168-w

INTRODUCTION

Perceiving the duration of events is a fundamental aspect of how we experience and interact with the world. As mentioned in the general introduction, our judgments about the duration of events can be influenced by various factors (Kanai et al., 2006; Matthews & Meck, 2016; Vatakis et al., 2018; J. Wearden, 2016), including the presence of external, previous or concurrent events. This phenomenon is particularly relevant in real-life situations where events rarely occur in isolation. Instead, they often overlap with other events, creating a complex temporal context that can affect our perception of time (Bryce & Bratzke, 2016; Jazayeri & Shadlen, 2010; Matthews & Meck, 2016).

One significant aspect of this complex temporal context is multiple timing, which refers to the interference caused by the combination of multiple temporal events that can bias our perception of time. This interference occurs even when the alternative events are not directly relevant to our task, or we are not actively paying attention to them. As described before, multiple timing can be categorized into two types: sequential multiple timing, where events occur one after the other, and simultaneous multiple timing, where events overlap in time.

To illustrate, imagine you are waiting in a queue. Observing how long other queues take to advance might affect how long you perceive your own queue to be stopped before advancing. Here the duration that is relevant for you, which is the time you expect will take for your queue to advance, will be determined by the duration it has previously taken to advance each time, which is the direct evidence, but it will also be shifted depending on the temporal context, the intervals other queues take to advance. Although independent, you might observe how long other queues also take to advance, and this might be integrated into your experience of time too and end up affecting your predictions. This is just an example that highlights how multiple timing can introduce perceptual noise and distort our time estimates, which will be even more influential when we are under conditions of more uncertainty.

Despite its relevance to real life, research on multiple timing has been relatively scarce and presents inconsistent findings. If we consider both simultaneous and sequential effects, we find studies reporting both repulsive and averaging effects from additional durations. This means that depending on the case, we could find that either the duration we are estimating or judging is shifted away from the other durations we are exposed to (Heron et al., 2012), or in other cases attracted, making us perceive this duration as more similar from one another (Burr et al., 2013; Kawahara & Yotsumoto, 2020). However, when events overlap in time, findings often lean towards the latter case, an averaging or assimilative tendency (Burr et al., 2013; Kawahara & Yotsumoto, 2020).

Given this context, we can hypothesize what effects multiple timing might produce from the perspective of some predominant models in time perception (as discussed in the general introduction). To give an example, imagine a situation where we are required to track the duration of a target event, but it overlaps in time with simultaneous events that have durations different than the target. Now we will discuss what each model would predict from this situation.

First, we could predict different outcomes from the basis of pacemaker-accumulator models depending on the variation we focus on. The attentional-gate model predicts that the presence of distractors could divert attentional resources from the main time-tracking task (Zakay, 2015; Zakay & Block, 1997). As a result, the attentional gate would shrink and let fewer pulses get through, leading to an overall underestimation of the target duration. Notice that this happens regardless of the distractors' durations, and it is only the presence of these additional stimuli that produces the effect. On the other hand, under the weighted sum of segments theory (Matthews, 2013) we could expect that distractors affect the perceived duration of the target only when the distractor duration is comprised fully within the target event, as it would divide it into different subsegments, but should not affect the perceived duration of the target when it is fully embedded within the distractors.

Alternatively, the ATOM (A Theory Of Magnitude) suggests that we use a similar perceptual mechanism across different modalities (Walsh, 2003). Therefore, if we know of effects from other modalities where perceived magnitudes are affected by the magnitude of surrounding stimuli, we should expect the same effects to take place with duration (Bratzke et al., 2023). For example, the well-known Ebbinghaus-Titchener (Ebbinghaus, Hermann, 1902; Titchener, 1901) size illusion shows how the size of irrelevant stimuli surrounding a target generates a repulsive effect where the target is perceived as smaller when surrounded by larger stimuli and vice versa (see Figure 3.1 for a visual example). According to ATOM, if we use the same mechanisms for duration and size processing and therefore, they should suffer from the same flaws. If we translate the paradigm of this illusion from size to duration, we should also find a repulsive effect, with the duration of central stimuli being underestimated when surrounded by stimuli of longer durations and overestimated when surrounded by stimuli of shorter durations.

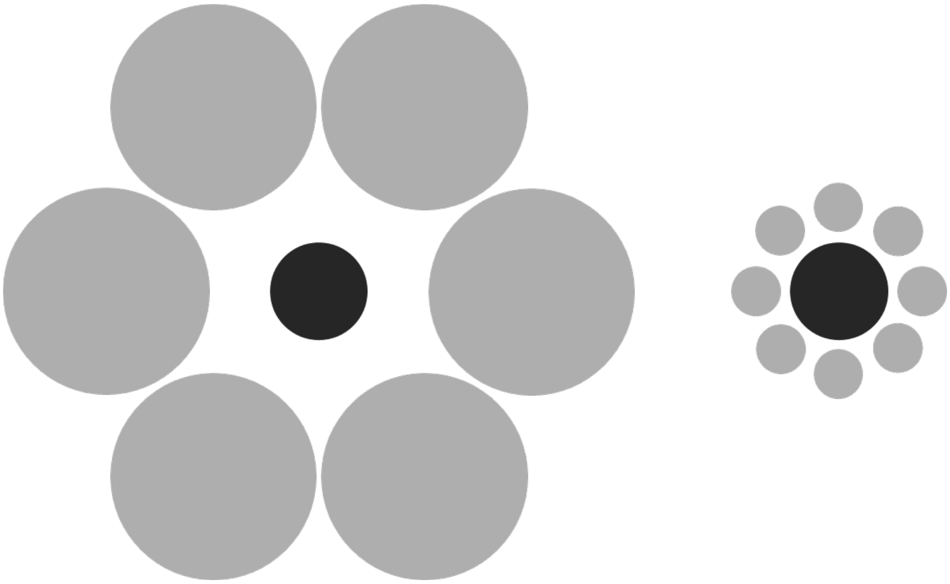


Figure 3.1. Example of the Ebbinghaus-Titchener illusion. The central (black) disks are of equal size, but due to the presence of bigger or smaller (grey) surrounding disks, they are perceived differently.

In contrast, the Duration-Channels model predicts something different. According to this model, specific neural channels are tuned to different durations, and the activation of these channels can influence the perceived duration of events (Bruno & Cicchini, 2016; Heron et al., 2012). When multiple durations are presented simultaneously, the channels corresponding to each duration are activated. Here, the residual activation from channels activated by the distractors could merge with those activated by the target event, causing intermediate channels to peak in activity and shift the perceived duration away from its accurate value (see Figure 3.2 for an example of these cases). Therefore, this results in an assimilative effect, with the target duration being shifted towards the duration of the simultaneous distractors. However, this model could also account for the repulsion effects due to adaptation (Heron et al., 2012), as these could be due to channel saturation, where repeated activation of a specific channel prevents subsequent stimuli of that same duration to signalled by the same channels.

Building on this foundation, we aimed to explore the effects that the durations of simultaneous but irrelevant events can have on the duration judgments of an attended event. To this end, we designed a novel task that translates the Ebbinghaus-Titchener illusion, traditionally a size perception illusion, to the temporal domain. In our task, participants compared the duration of two central targets of equal duration, accompanied by simultaneous distractors with either longer or shorter durations. Following the same rationale as the size illusion, by using the same duration for both targets of the comparison we could assume that any shifts in duration judgments should be attributed to the influence of the distractor durations.

Due to the fact that the Duration-Channels model seems to better fit the findings in the literature on multiple timing, as it can accommodate both averaging and repulsion effects, we delved deeper into this model and developed a computational approach to analyze our findings.

Based on the evidence of simultaneous multiple timing, we hypothesized that the duration judgments of the targets would be biased towards the durations of the distractors, consistent with a central tendency effect. Additionally, since there is evidence that effects from simultaneous stimuli tend to decay as the durations become more different(Burr et al., 2013; Heron et al., 2012), we aimed to test the duration-channels model by estimating a leaking factor that modulates the influence of distractors based on their similarity to the target duration.

This simple yet innovative approach not only aimed to elucidate how simultaneous distractors influence duration perception but also to provide valuable insights into the mechanisms of time perception and how they may parallel those underlying size perception.

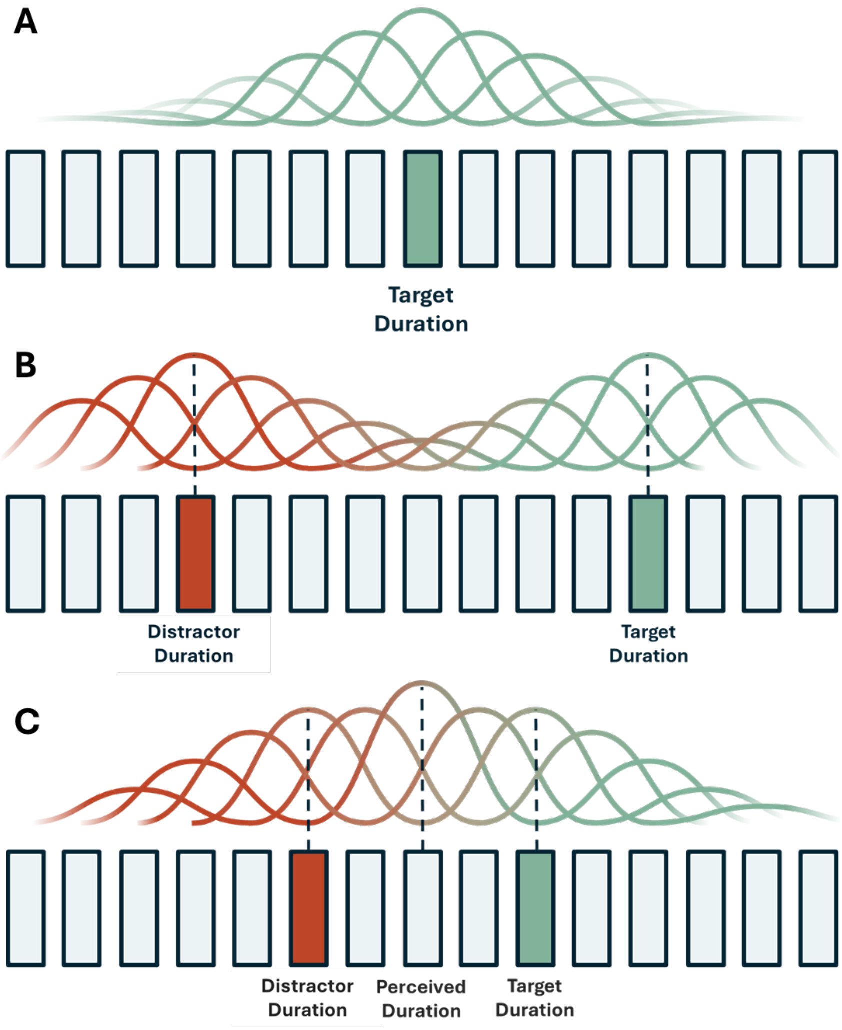


Figure 3.2. Representation of the duration-channels activation by different stimuli. ***(A)*** *Activation of the channels with preference for the target duration.* ***(B)*** *Different durations activate differential channels.* ***(C)*** *The residual activity from the different durations can merge and peak at an intermediate duration.*

Duration-Channel Leaking model

To further explore how distractors' durations affect the perceived duration of overlapping targets, we developed a novel computational model grounded in the duration-channels theory. To summarize, this theory posits the existence of neural pathways (channels) that are selectively responsive to specific time intervals (Heron et al., 2012).

The model hypothesizes that not only actively tracked but also unattended events can activate these channels. This combined activity is what could explain the effect of distractor durations on the perceived duration of a target. If the distractors activate close channels to the target duration, the integration of this activity in the time estimates might result in an averaging or central tendency effect, which goes in line with the findings of simultaneous multiple timing studies.

The model also suggests that the magnitude of this effect depends on the similarity between stimuli. The closer the duration channels are, the stronger the interaction will be between them (As seen in Figure 3.2 B and C). We assume that this happens because the distractors activate the channels associated with their durations, and this activation leaks into the processing of the target duration. The strength of this leakage diminishes as the difference between target and distractor durations increases.

We modelled an integration function that works as a weighted average where both target (t) and distractor (d) durations are combined. The weight (w) of the distractors determines to what extent the distractor duration will determine the perceived estimate of the target duration ($\hat{t}$).

$$\hat{t} = \frac{(t + d \cdot w)}{(1 + w)} \qquad (3.1)$$

The weight (w) of the distractors ranges from 0 to 1, being 1 a maximum interference where the distractor has as much relevance as the target duration and 0 meaning a null effect from the distractors, with the estimation being based only on the target duration. The weight is determined by how close the target and distractors are, with more similarity leading to a higher weight. This relation is modulated by a leaking factor (k) according to the weight function:

$$w = k^{|d-t|};\ 0 \leq k \leq 1 \qquad (3.2)$$

The leaking factor (k) can also have values ranging from 0 to 1 and determines the rate at which the distractor's weight decays as its duration becomes more different from the target duration. This component allows for a variability of cases. For example, distractors could keep their weight regardless of its difference with the target duration when k approaches its maximum of 1. Alternatively, when k is closer to 0, the distractor weight decays very rapidly as the difference increases, and only those distractors with durations very similar to the target are able to induce any effect.

See Figure 3.3 for an example of how different leaking factors produce varied shapes of weight function, which in turn modulates how the perceived duration of a target is affected by distractors of different durations.

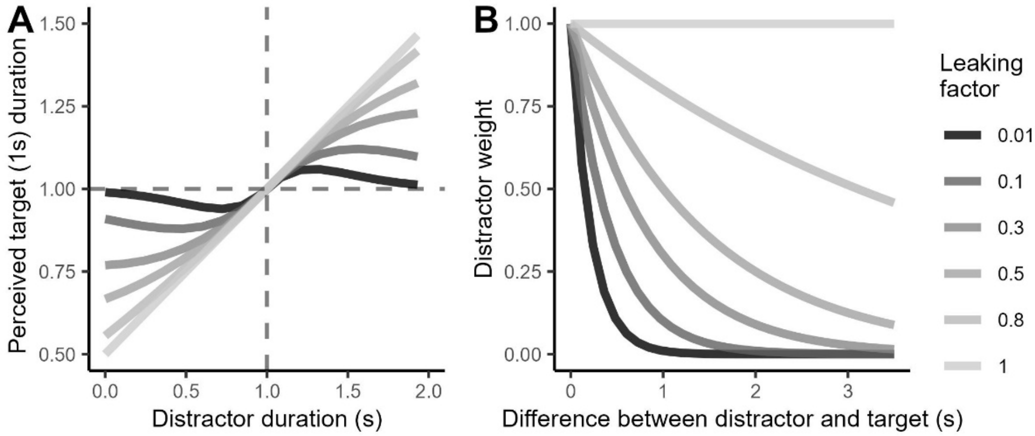


Figure 3.3. ***(A)*** *Perceived duration of a 1s target as a function of the duration of simultaneous distractors.* ***(B)*** *Weight of the distractors as a function of the difference between target and distractor durations. With smaller leaking factors the weight decays more rapidly and the perceived target duration goes back to its original value.*

METHODS

Participants

The sample of the first study consisted of twenty-two participants, 15 of them self-identified as female and 7 as male (mean age = 25.23, SD = 2.89). All of them had normal or corrected-to-normal vision and were naïve to the purpose of the experiment. The study is part of a research program that has been approved by the ethical committee of the University of Barcelona (IRB00003099) according to the principles stated in the Declaration of Helsinki. All participants gave written informed consent to participate in the experiment.

Apparatus and stimuli

The task was designed and conducted using Psychopy software (Peirce, 2007) on a Mac Pro. Stimuli were presented on a 24.5-inch ASUS ROG Swift PG258Q monitor using a resolution of 1920 × 1080 pixels and at a 240 Hz refresh rate. Participants performed the task on a chinrest at 57 cm of the screen.

The visual stimuli used for the task were white blobs (maximum luminance of 226.2 cd/m2 with a raised cosine mask of a full diameter of 4.5 deg and a central plateau of 4 deg) presented against a grey background (mean luminance of 55.38 cd/m2).

The presentation consisted of a combination of one blob presented at the centre (target stimuli) along with an array of four blobs at each cardinal point (top, right, bottom and left of the centre) with 9 deg of eccentricity.

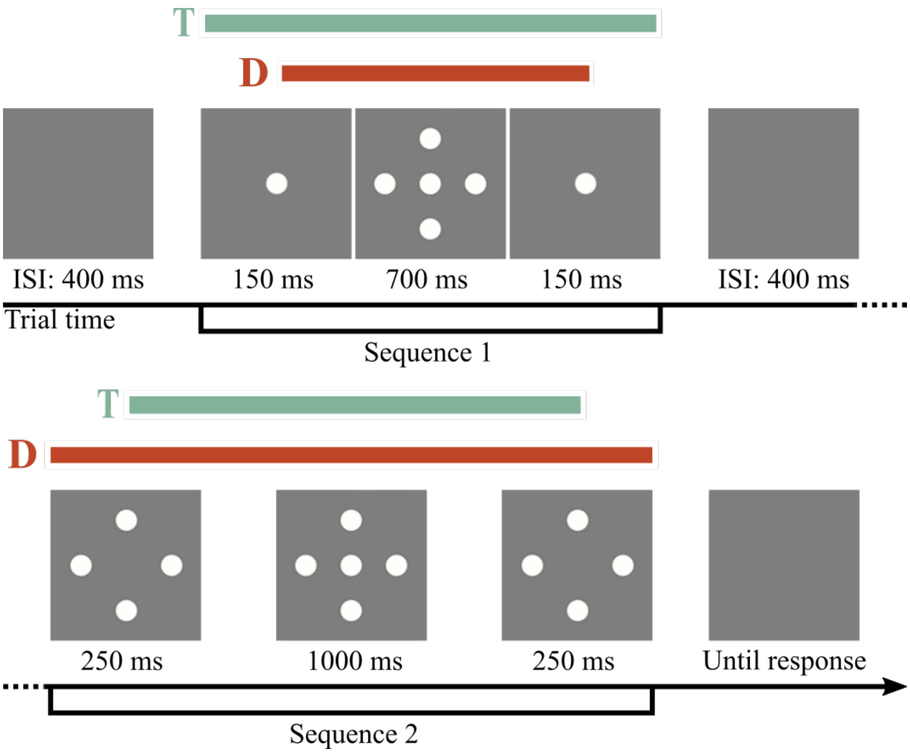


Figure 3.4. Example of a trial with 700 ms distractors (Sequence 1) paired with 1500 ms distractors (Sequence 2). The target in both sequences lasted 1000 ms, and they were centred with the distractors at each sequence.

Procedure

Duration Judgment Task

Participants were instructed to observe two sequences presented one after the other and compare the duration of specific target stimuli from each sequence (see Figure 3.4).

After viewing the sequences, they responded by pressing the left arrow key if they perceived the target stimuli in the first sequence as lasting longer, or the right arrow key if they perceived the target stimuli in the second sequence as lasting longer. A 400 ms blank interval was interleaved before and after each sequence.

Three different conditions were employed, that differed in which elements were considered as target stimuli:

- *Distractors Condition*: Each sequence comprised a central target and four surrounding distractors (all of them blobs of the same size, colour and luminance). Participants were asked to focus solely on comparing the duration of the central targets, ignoring the surrounding distractors. The central target duration was always set at 1000 ms for both sequences. The distractors within each sequence had uniform durations of either 300 ms, 700 ms, 1500 ms, or 3000 ms, which were the same for all the distractors of the same sequence but different between the two sequences. To ensure that target and distractor durations overlap, their onsets and offsets were adjusted so that they were centred in time (see Figure 3.4 for an example).
- *Ensemble Condition*: The stimuli and sequences were identical to those in the Distractors condition, but participants were instructed to compare the duration of the entire array of blobs from each sequence. This meant considering the target to span from the appearance of the first blob to the disappearance of the last blob, regardless of whether they were the central or surrounding blobs. Thus, all stimuli were considered part of the target in this condition.
- *Control Condition*: Each sequence contained only one central target blob. The target durations in each sequence were 300 ms, 700 ms, or

1500 ms in varying combinations, always differing between the two sequences in a pair.

Each participant was presented with 30 repetitions of each combination of sequences at each condition in a randomized order. Each condition was divided into five short blocks. Participants could take short, self-timed breaks between blocks. Each participant completed all three conditions in a counterbalanced order.

Predictions

The Control and Ensemble conditions were used to verify whether participants could accurately discriminate the durations selected for this task. The psychometric functions of each participant were analysed. Comparisons between these conditions were used to identify differences in duration discrimination when time intervals consisted of either single or multiple elements.

The effect of distractors on judged durations was then examined in the Distractors condition. It was expected that the distractors would induce a central tendency effect. By fitting a psychometric curve to the responses in this condition, based on the difference in distractor durations, the slope's sign was derived to indicate either repulsion (negative) or central tendency (positive).

If a central tendency effect was found, the Channel Leaking model was applied to obtain each participant's leaking factor, assessing how well the model described their response patterns.

Additionally, the relationship between the leaking factor and preservation of discrimination capacity when time intervals included multiple elements was explored. The leaking factor, which is an indicator of the extent to which participants were affected by distractor durations (considered a source of noise), was predicted to be inversely correlated with performance on discrimination thresholds. A smaller leaking factor, suggesting better inhibition of perceptual noise introduced by distractors, was expected to correlate with better performance.

RESULTS

Control and ensemble conditions

First, we checked that all participants were able to discriminate between the different durations that we will be using for the distractors condition. If participants were unable to distinguish the different durations, we would not even expect that presenting different distractor durations would have any differential effect. Also, we compared participants' discriminability when comparing events presented through a simple visual element or when these events were composed of multiple elements with different onsets and offsets.

To assess participants' discriminability, we fitted psychometric curves to each individual participant's data from the Control and Ensemble conditions using the logistic function. The models were fitted with the proportion of "Second interval lasted longer" responses as a function of the difference between the second and first interval durations.

We used maximum likelihood estimation (MLE) with the Quickpsy package (Linares & López-Moliner, 2016) for R software (R Core Team, 2020) to estimate the point of subjective equality (PSE) and the slope of the curve as free parameters as well as the 95% confidence interval by using bootstrap (Efron & Tibshirani, 1993). Since these could be affected by the lapse rates, which refer to the probability of participants making random errors (Prins & Kingdom, 2018; Wichmann & Hill, 2001), we included it too as an additional free parameter and kept it for modelling those participants in which the fit improved according to the Akaike information criterion (AIC).

While the PSE can be used as a measure of accuracy to measure precision we derived the standard deviation of the psychometric function from its slope. This measure of duration discrimination will then represent participants' ability to differentiate between different durations, with smaller values representing better sensibility and vice versa.

In terms of accuracy, we found that participants were able to discriminate between the different intervals in up to 95% of trials in the Control condition and 86% in the Ensemble condition (see Figure 3.5). This shows that although being able to discriminate well in most cases, it was slightly harder to measure and compare the durations when they were composed of multiple stimuli than when it was only delimited by one element. Also, the PSE of the psychometric curves fitted to each participant informs us of any general bias in the duration judgements (for example, being more prone to judge the first or the second interval as longer). Globally, there is no clear pattern of bias between participants nor difference in the general direction of biases between conditions, but there is an increased variability of these biases in the Ensemble condition (see Figure 3.6C). We suggest this increase in the magnitude of bias could come from the increase in perceptual noise due to the composition of the intervals from multiple elements, which might cause participants to rely more on their own biases rather than the evidence.

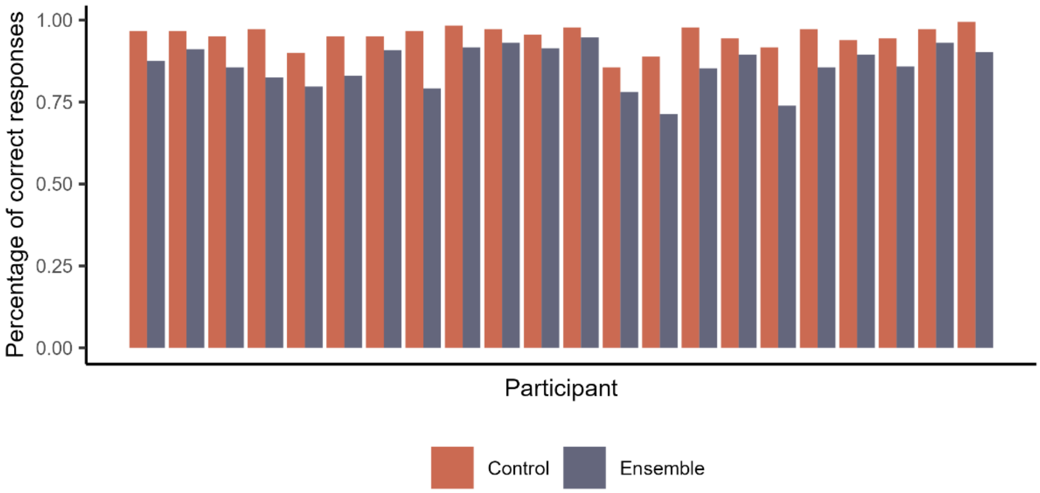


Figure 3.5. Participants' percentage of correct discriminations in the Control and Ensemble conditions.

On the other hand, the precision of these judgments was assessed through the standard deviation (SD) of the psychometric curves. We found greater SD ($t(21) = -8.657$, $p < 0.001$) in the Ensemble condition (mean = 1.13, SD = 0.477) than the Control (mean = 0.35, SD = 0.126) condition (see Figure 3.6D). This increase reflects that participants needed a greater difference in duration between the two intervals in order to discriminate them in the Ensemble condition. Again, the perceptual noise caused by having to measure the interval across the presentation of multiple elements could also be impairing participants' capacity to discriminate well in this range of durations.

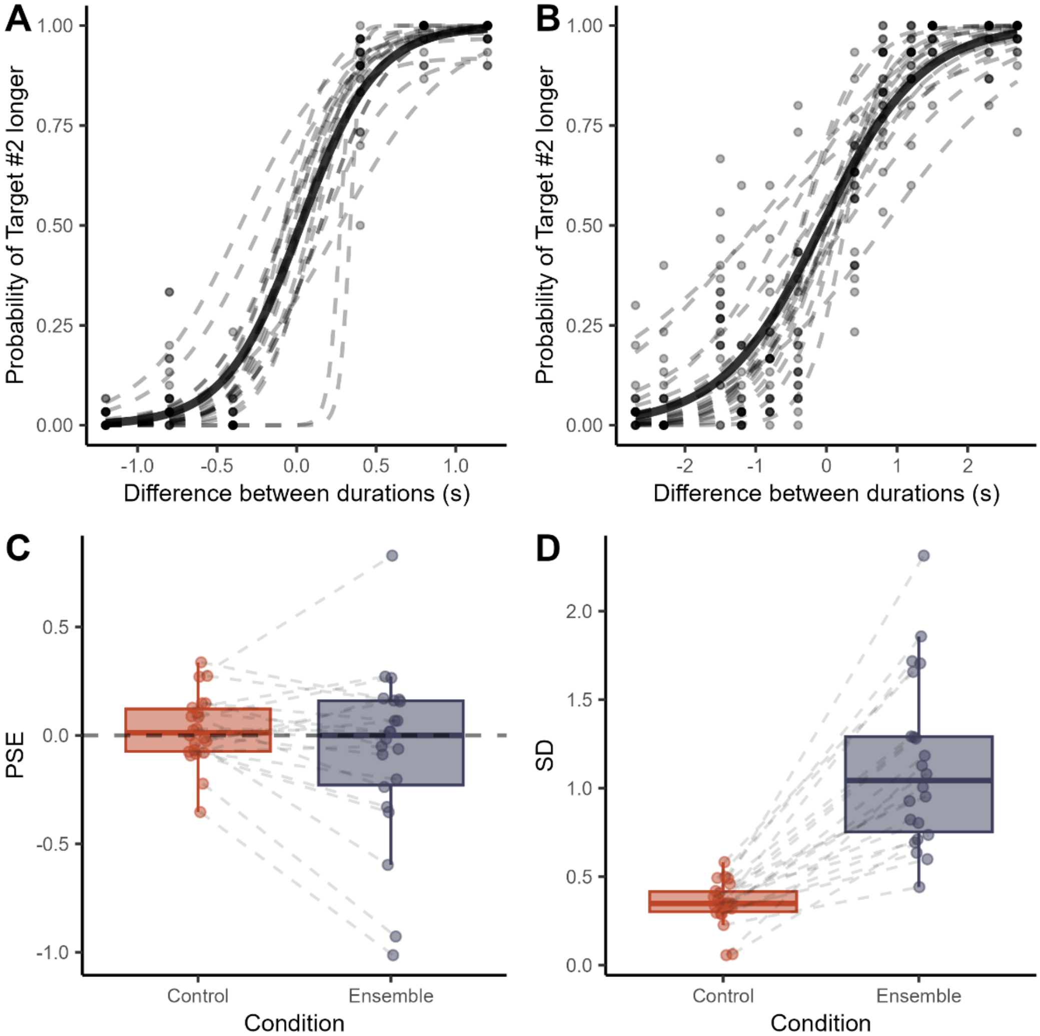


*Figure 3.6. Psychometric functions from the control **(A)** and ensemble **(B)** conditions. Dashed lines represent the functions of each participant, solid lines show the fit of the aggregated data from all participants. Comparison of the estimated Point of Subjective Equality (PSE) **(C)** and Standard Deviation (SD) **(D)** of the curves from each participant at the Control and Ensemble conditions.*

Distractors condition

Following the same process, we fitted the psychometric function of each participant in the Distractors condition. In this case, we aimed to determine if the duration judgments of the targets could be influenced by the distractor's duration. Here we want to highlight that what we are interested in is not only the effect of the presence of a distractor element but whether the time properties of this element could be integrated into the temporal processing of the target. To this aim, we fitted the probability of responding "The target within the second sequence lasted longer" as a function of the difference between distractors (distractor duration of the second sequence – distractor duration of the first sequence).

We then used the slope of the fitted curves to determine the direction of the effect (if any) caused by the distractors. In this case, a positively signed slope would indicate that targets surrounded by distractors of longer duration are perceived as longer, which could be interpreted as a central tendency effect. On the other hand, a negative slope would indicate that targets surrounded by longer-duration distractors are perceived as lasting longer, suggesting a repulsion effect. If none of these effects would prevail, the slope of the psychometric function should appear non-different from 0.

We found that none of the participants' 95% confidence interval (CI) of the slope included 0, suggesting that their judgments of the central target were systematically influenced by the distractors' durations. Positive slope values were found in 19 out of 22 participants, indicating a central tendency where target durations were perceived as more similar to the distractors' durations. In contrast, three participants showed negative slope values, indicating a repulsion effect where the judged durations of targets diverged from the durations of the distractors. See Figure 3.7 for a detail of the slopes obtained from each participant and Figure 3.8 for examples of strong and weak patterns of central tendency and repulsion found within our sample.

Since most participants showed a central tendency, which aligns with the assumptions of the Channel Leaking model, those with repulsion tendencies were excluded from the estimation of the leaking factor that followed.

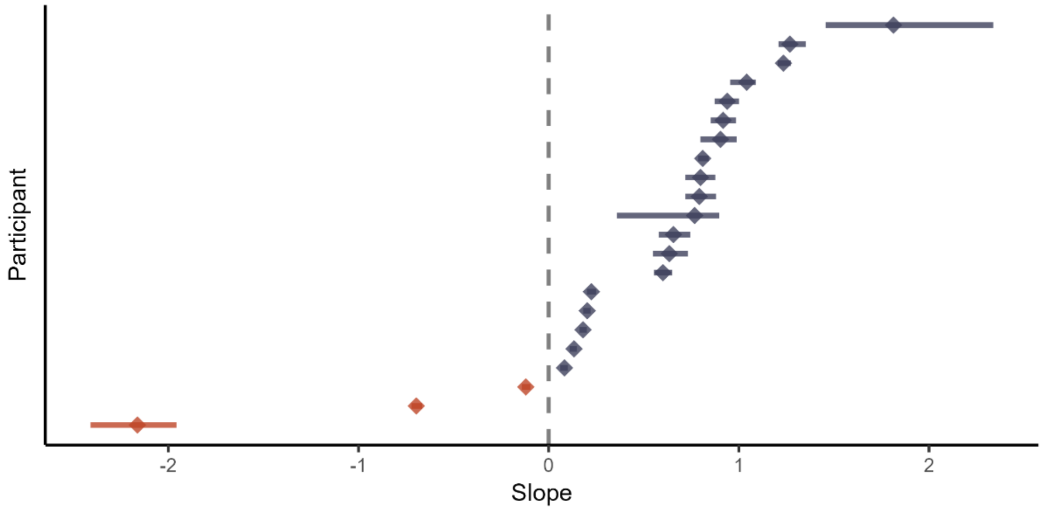


Figure 3.7. Distribution of slope estimates (points) and 95% confidence intervals (brackets) obtained for each participant in the distractors condition. Most participants presented a positive slope value (in blue) while a small group presented a negative slope (in red).

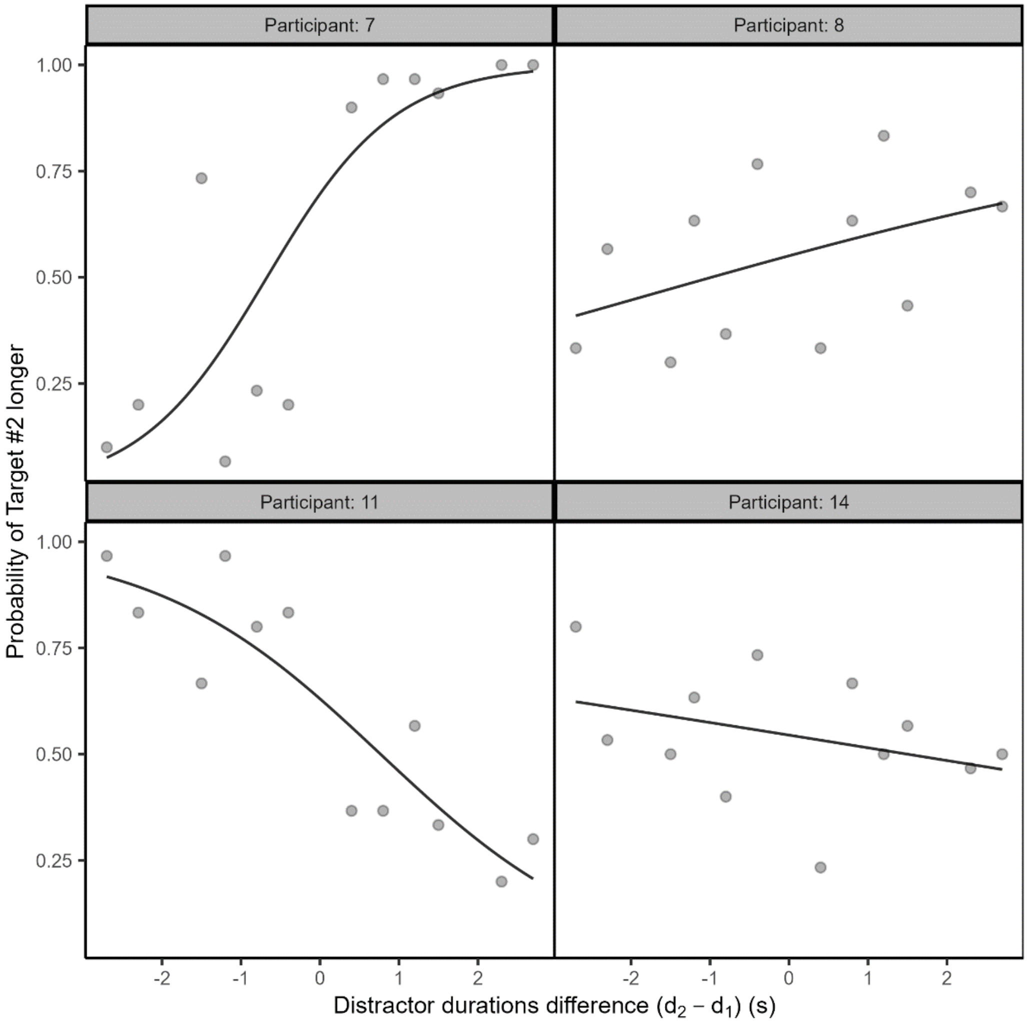


Figure 3.8. Examples of 4 psychometric functions of representative participants with high (left column) and low (right column) slopes and positive (upper row) and negative (lower row) slope signs.

Duration-channel Leaking model

Using the data from participants who exhibited a central tendency, we estimated the leaking factor (k) by applying Maximum Likelihood Estimation (MLE). This approach predicts the probability of response judgment for each combination of distractor durations. The optimization process maximized the log-likelihood across each different combination of distractor duration (S) for every value of k:

$$LL(k) = \sum_{i=1}^{S} \binom{n_i}{m_i} + m_i \cdot \log(\varphi_k) + (n_i - m_i) \cdot \log(1 - \varphi_k) \quad (3.3)$$

Where n_i is the number of presentations of each combination of distractors and m_i is the number of times a participant judged the second target as longer. φ_k represents the standard Gaussian distribution (mean of 0 and SD of 1), which takes as an argument the difference in perceived durations between the two targets and computes its probability of that difference.

$$\varphi_k = \mathcal{N}(\hat{t}_2 - \hat{t}_1) \quad (3.4)$$

Here, the leaking factor k is already embedded in Equation (3.4 as each perceived target duration is integrating the distractor duration according to its weight, which is at the same time determined by the leaking factor.

$$\hat{t} = \frac{(t + d \cdot w)}{(1 + w)} \quad (3.5)$$

$$w = k^{|d-t|}; 0 \leq k \leq 1 \quad (3.6)$$

We used this model to estimate the *k* parameter for each participant that better fitted their data. We found a wide range of *k* values (mean = 0.46, SD = 0.312, from participants with a leaking factor of 0.006 that were very good at ignoring distractors to participants with a leaking factor of 0.999 that were fully misguided by distractor durations (see Figure 3.9).

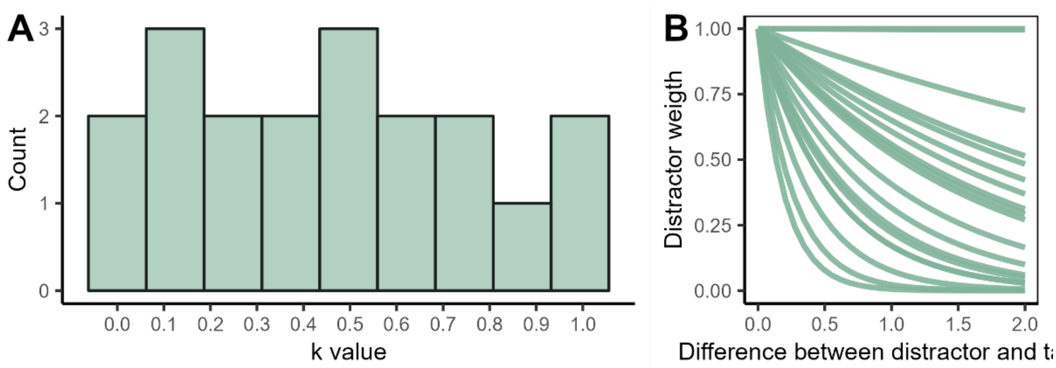


Figure 3.9. Estimated leaking factors from all participants. ***(A)*** *The proportion of leaking factors is quite uniform, covering all the range of possible leaking.* ***(B)*** *Weight functions calculated from the estimated leaking factor of every participant show a very varied casuistry.*

We then compared the predicted response probabilities with the observed data to evaluate the goodness of fit. Figure 3.10A shows the predicted distractor weights (w) for three participants with high, medium, and low k values. These curves illustrate how the weight of the distractor decreases as the difference between target and distractor durations increases, with the rate of decrease varying according to the leaking factor. Figure 3.10B displays the observed duration judgments (dots) alongside the predicted probabilities (solid line) of judging the second sequence's target as longer, based on the difference in durations between distractors of each sequence. The grey dashed line indicates that if distractor durations are ignored or not present, the predicted probability of judging the second target as longer is 0.5. Figure 3.10C shows how the predicted probability of judging the second target as longer (represented in a colour scale) varies for different combinations of distractor durations. The heat maps show the predicted response probabilities, while the circles indicate the observed probabilities. The more similar the circle colours and the background are, the better the fit between predicted and observed probabilities.

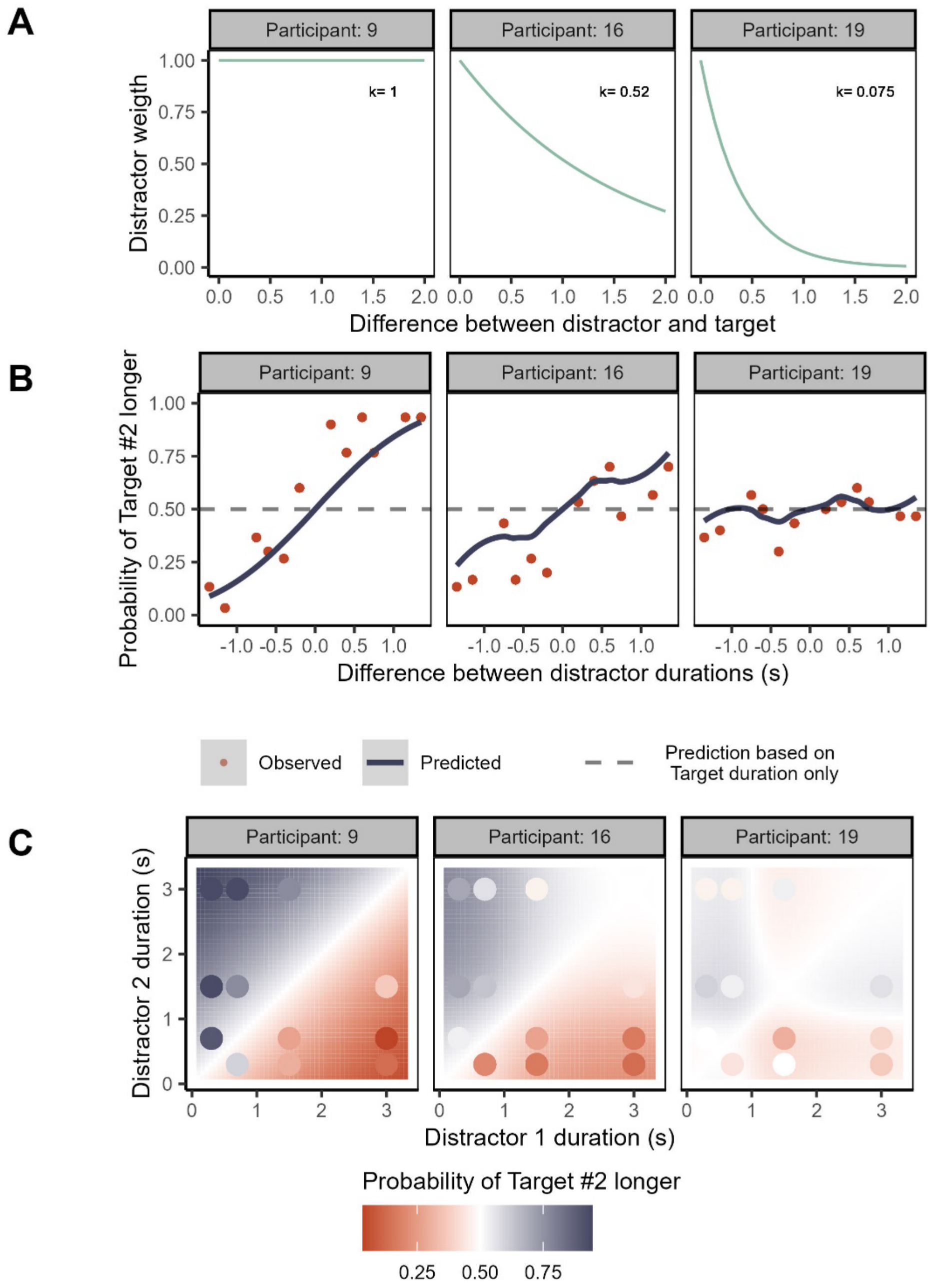


Figure 3.10. Sample of three representative participants with high medium and low values of leaking factor. ***(A)*** *The weight function shows how distractor weight decays differently depending on the leaking factor.* ***(B)*** *Predicted and observed responses get more biased with a greater leaking factor.* ***(C)*** *For any combination of distractors, the model's predicted probabilities of response (background colour) fit the observed data (coloured circles).*

We performed a chi-square test within participants to determine if the predicted response proportions from the model differed significantly from the observed ones for each combination of distractor durations. For most participants (14 out of 19), there was no significant difference between predicted and observed data. Table 3.1 lists the fit parameters for each participant. The predominantly good fit of the model indicates that the estimation of the leaking factor proved useful to predict the effects of the distractor durations on our participants despite the varied casuistry amongst them.

ID	χ^2(df, N)	*p*	ID	χ^2(df, N)	*p*
1	31.49 (11,30)	<0.05	12	14.85 (11,30)	0.190
2	13.01 (11,30)	0.293	13	30.72 (11,30)	<0.05
3	7.54 (11,30)	0.754	15	23.27 (11,30)	<0.05
4	21.74 (11,30)	<0.05	16	7.32 (11,30)	0.773
5	8.55 (11,30)	0.664	17	7.33 (11,30)	0.772
6	11.52 (11,30)	0.401	18	5.5 (11,30)	0.905
7	39.5 (11,30)	<0.05	19	3.33 (11,30)	0.986
8	18.4 (11,30)	0.073	20	17.91 (11,30)	0.084
9	9.62 (11,30)	0.564	21	14.57 (11,30)	0.203
10	7.4 (11,30)	0.766			

Table 3.1. Chi-square test parameters by participant.

Repulsion effects

Based on our data, a limitation of how we formulated the duration-channel leaking model (as in (3.1)) is that it strictly predicts a central tendency. However, we found that this was not the only result of our participants, some of which showed the opposite effect. To still be able to explain these findings, the model should allow for some process of inhibition between duration-channels. If this was the case, the activation of the channels from the distractors would inhibit the activity of neighbouring channels. To explore this idea, we formulated and tested an alternative version of the duration-channel leaking model that, instead of using an averaging function to compute the weight of distractors, uses a Ricker wavelet function:

$$w = \left(1 - \left(\frac{d-t}{k}\right)^2\right) \cdot 2^{-\frac{(d-t)^2}{k^2}};\ k > 0 \qquad (3.7)$$

Here, the weight (w) can also include negative values, which mathematically produce the repulsion effect. Also, in this case, the leaking factor can take any value greater than 0. The explanation is that with this model, duration differences that are closer generate a central tendency, up to a point where this effect shifts and becomes a repulsion effect and that finally decays to no effect. Now, the value of the leaking factor (k) does not represent the strength of the decay of distractor weight, but the duration difference at which the effect shifts from averaging to repulsion. For example, with a leaking factor of k = 0.3, we would find that distractors would induce an averaging effect that gets weaker until it reaches the duration difference of 0.3 s, moment at which the effect gets stronger again but in the opposite direction, with a repulsion tendency, following by a general decay with the effect approaching 0 with longer duration differences (see Figure 3.11 for an example).

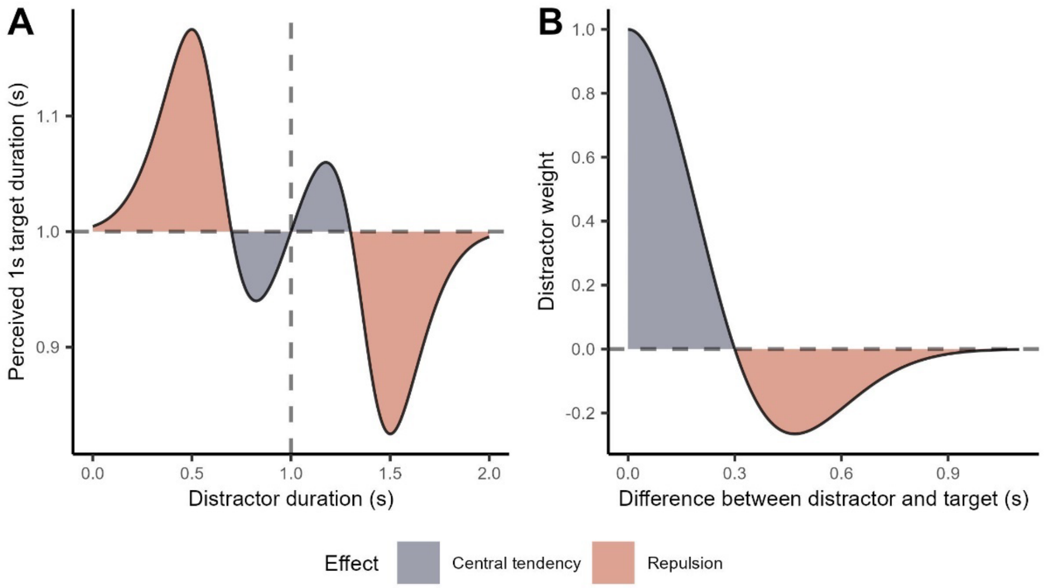


Figure 3.11. Example of the adapted model for repulsion with k of 0.3. Red and blue areas represent ranges where repulsion and central tendency effects are expected. ***(A)*** *Perceived duration of a 1s target as a function of the duration of distractors.* ***(B)*** *Weight of the distractors as a function of their difference with the target duration. Negative weights operate the same as positive weights but with repulsion.*

Following the same procedure as we used to test the original model, we fitted this alternative model to those participants that originally showed a repulsion effect. Notice that this model has the same number of parameters as the previous version, and only differs in the function and interpretation of the leaking factor.

Two out of three participants showed a non-significant difference between predicted and observed responses after obtaining the best fitting *k* estimate (using MLE), indicating a good fit of the model. This modification suggests that the effects of multiple timing found in almost all participants could still be explained under the basis of the duration-channel leaking model.

ID	χ^2(df, N)	*p*
11	31.85 (11,30)	<0.05
14	17.99 (11,30)	0.082
22	19.48 (11,30)	0.053

Table 3.2. Chi-square test parameters by participant using the modified weight function.

Sensitivity to noise

We also aimed to determine whether the leaking factor could be associated with the ability to filter out perceptual noise, which in our task is manifested as the capacity to maintain duration discriminability when time intervals consist of multiple elements rather than a single one.

Understanding how the leaking of the channels relates to the voluntary integration of information could be very informative and help us understand how helpful or harmful this leaking can be to our temporal processing of complex events. Here we might ask whether being more susceptible to being influenced by a wider range of distractors (manifested through a greater leaking factor), correlates with the impairment in discriminability of a specific duration due to the event being presented as the composition of multiple events (difference in discriminability of durations composed by single vs multiple events).

To assess this, we used the ratio of variances from the Control and Ensemble conditions ($\sigma^2_{Control}/\sigma^2_{Ensemble}$) to represent the tolerance to perceptual noise. These variances are derived from the slopes of the psychometric curves of each condition. A ratio closer to 1 indicates that duration judgments with multiple stimuli are practically as accurate as those with a single stimulus of the same duration. On the other hand, as the ratio goes closer to 0 it suggests a greater impairment in discriminability due to the increased number of stimuli to be tracked because the variance in the ensemble condition would be much greater than that of the control condition.

Although we found a correlation between the variance ratio and the leaking factor ($r(17) = 0.33$, $p = 0.165$), it was not statistically significant. However, after excluding one participant with extremely high sensitivity in the Control condition (resulting in a final sample size of N=18), the correlation actually became significant ($r(16) = 0.49$, $p = 0.039$). These correlations are illustrated in Figure 3.12.

Interestingly, this positive correlation initially contradicted the expected relationship between these variables. The positive trend indicates that higher leaking factors are found when although increasing the number of stimuli that compose an event discriminability is preserved (also higher variance ratios).

With this, the ability to discriminate durations that are not defined by one single stimulus but rather by the succession of overlapped events would be linked to greater permeability of duration channels sensitive to more different durations. Observers who are more prone to involuntarily integrate the durations of surrounding distractors are also better at attending and measuring the duration of an interval composed of multiple and different events. Conversely, participants who struggle with processing durations that require tracking multiple sources of stimulation (indicated by a lower variance ratio) are on the other hand less affected by irrelevant distractors overlapped with a target event (lower leaking factor).

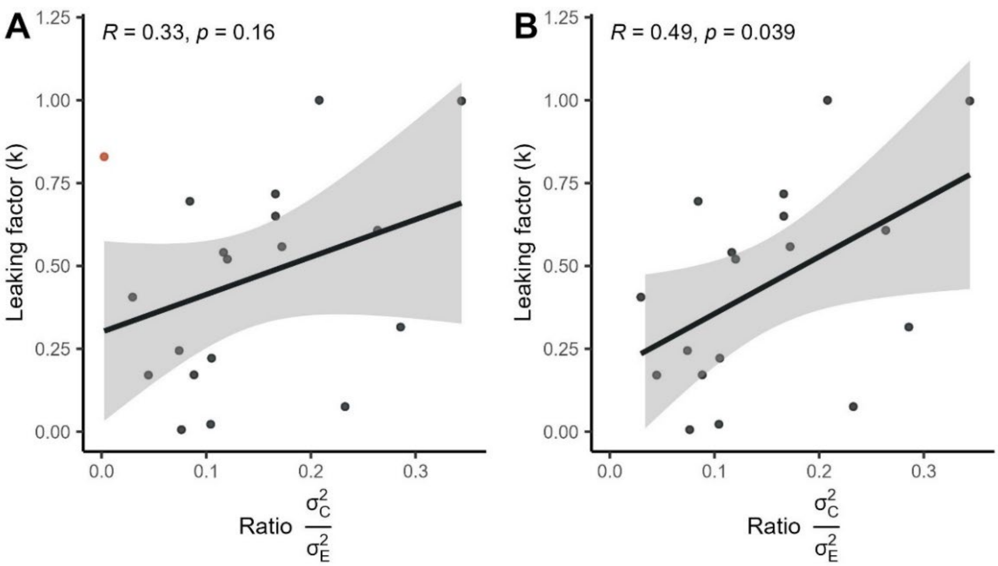


Figure 3.12. Correlation between leaking factor and ratio of variances. ***(A)*** *Data from all participants with central tendency with an outlier participant highlighted in red,* ***(B)*** *Updated correlation excluding the outlier participant.*

DISCUSSION

This study aimed to provide significant insights into the phenomenon of multiple timing, specifically about how overlapping intervals can introduce perceptual noise and bias our time judgments of task-relevant events. Our findings demonstrate that simultaneous distractors systematically influence the perceived duration of target events, supporting the concept of a central tendency effect. This aligns with previous studies suggesting that our perceptual system tends to average temporal information in the presence of simultaneous stimuli (Burr et al., 2013).

We also proposed a computational model based on the duration-channels theory to explain how the information from distractors is integrated into the perceptual decision process.

Previous literature about multiple timing has shown how recent or concurrent information can affect reproductions and duration judgments. In this regard, different types of effects have been found according to different frameworks and paradigms. For example, Bayesian studies propose that time estimations under conditions of uncertainty are often biased towards a general average of the contextual evidence (Hallez et al., 2019; Jazayeri & Shadlen, 2010; Wehrman et al., 2020; Wiener et al., 2014). Moreover, studies focused on simultaneous multiple timing also revealed interferences that generate averaging tendencies (Ayhan et al., 2012; De Corte & Matell, 2016; de Montalembert & Mamassian, 2012; Kawahara & Yotsumoto, 2020). However, adaptation studies, which provoke a saturation of a specific duration, often report a repulsive or contrastive effect, in which the perceived duration is shifted away from the physical duration after saturation (Heron et al., 2012; Maarseveen et al., 2017, 2019).

To explore this and bring further evidence in a simultaneous duration paradigm, we designed a perceptual decision task where participants had to compare the duration of two stimuli that were overlapped in time with concurrent distractors of longer or shorter duration. This task, which induced a high degree of uncertainty in the comparison between the target durations due to both having exactly the same duration, focused on understanding the distractor's role in the perceptual process. Therefore, any systematic bias in the judgment of the targets could be related to the difference in duration between the simultaneous but in principle irrelevant distractors that accompanied each target.

First, we compared performance in the Ensemble and Control conditions. We found that participants discriminated better durations that were delimited by the presentation of only one element, whereas the same durations composed by multiple elements were harder to discriminate. This shows that having to track multiple sources of information imposes an increase in perceptual noise, which hinders timing performance.

We then wanted to assess whether the presence of multiple elements could still have an impact when these were irrelevant to the task. In the Ensemble condition, all elements were part of the target and should therefore be attended. On the other hand, in the Distractor condition they represent something different, here participants should only attend and compare the central element while ignoring the rest, which changes the role of the surrounding stimuli from being part of the target to being part of the temporal context. What was relevant for the task in the Ensemble condition should be ignored in the Distractor condition.

We found that despite instructions to ignore the distractors, participants' responses systematically varied with the duration of the surrounding stimuli. More specifically, the majority of participants showed a tendency to judge the target duration as more similar to the distractor duration than it actually was. Consistent with the studies that reported averaging or central tendency effects with simultaneous information (Ayhan et al., 2012; De Corte & Matell, 2016; de Montalembert & Mamassian, 2012; Kawahara & Yotsumoto, 2020), we also found that under uncertainty, estimations shifted towards a central value from the immediate temporal context.

Interestingly, a small number of participants exhibited the opposite effect, a repulsion tendency where participants judged the target as lasting shorter when distractors lasted longer and vice versa. These contrasting results go in line with those found in adaptation studies, where participants' duration estimates shifted away from the duration that was repeatedly presented earlier (Heron et al., 2012; Maarseveen et al., 2017, 2019). However, it is questionable whether the repulsion effect we found in our paradigm and the one observed in adaptation paradigms rise from the same mechanisms. Adaptation studies typically rely on the saturation of a specific magnitude of stimulation, whereas our stimulus presentation does not depend on such saturation but can appear with just one presentation. Therefore, we suspect different mechanisms underlying the repulsion effect we found than those found in adaptation studies.

Our findings highlight the fact that different tendencies can emerge within the same paradigm and point out yet unknown factors that influence duration processing and judgments. One potential explanation for the coexistence of both types of outcomes could be related to what is proposed by carryover effect studies; that the cognitive nature of the interfering information can determine the direction of the effect, relating central tendency effects to decisional factors and repulsion or contrastive effects to perceptual factors (Wehrman et al., 2020; Wiener et al., 2014). Still, studies have shown that both sensory and decisional components can contribute to biases measured by psychometric functions (Linares et al., 2019), suggesting that a combination of these factors in our task could be possible. Unfortunately, our data does not conclusively indicate which type of bias (perceptual or decisional) might be predominant in our paradigm.

This unforeseen combination of results highlights a limitation of our initial formulation of the duration-channels model. Initially, it assumed central tendency effects, calculated through a weighted average and the leaking function. To address this issue, we proposed an alternative weight function formulation that allows both repulsion and central tendency effects due to lateral inhibition (Blakemore et al., 1970; O'Toole & Wenderoth, 1977) while still keeping the assumption of a decay of interference strength as durations separate enough. This modification enabled us to predict the response patterns of those participants exhibiting repulsion effects. However, we believe that further research is needed to develop a unique model that fully accounts for both central tendency and repulsive effects, each considering the contribution of perceptual and decisional components.

Another important consideration for the validity of the model lies in how the proposed model aligns with the scalar property of timing or Weber's Law, which remains a key criterion for any timing model. It states that the Just Noticeable Difference (JND) between two stimuli is proportional to the magnitude of the stimuli, which implies that for larger time intervals, the thresholds for detecting differences should increase proportionally.

Our initial formulation of the model (Equation (3.1) suggests a linear relationship between physical duration and perceived duration in the absence of distractors (i.e., when d=0 and w=0). At first glance, this linear relationship seems to contradict Weber's Law which usually, but not always, suggests a logarithmic perceptual scale. Nevertheless, Weber's Law could still hold under our model if we consider the type of noise affecting duration perception (Hass & Herrmann, 2012). If the noise is additive (constant regardless of stimulus magnitude), then a logarithmic scale would be necessary. However, if we assume that the noise is multiplicative (increasing with the duration magnitude), a linear perceptual scale can still be consistent with Weber's Law (Kingdom & Prins, 2016). In this scenario, the JND would increase proportionally with the physical duration, maintaining the proportionality required by Weber's Law. Furthermore, empirical evidence from Stevens' Power Law (Stevens, 1957) for duration estimation judgments reports an exponent close to 1 (approximately 0.91), indicating a nearly linear relationship between perceived and physical durations (Kane & Lown, 1986). This supports the idea that a linear perceptual scale can be a valid approximation, even within the framework of Weber's Law.

Regarding how the duration of distractors interfered with the perceived durations of the target, we assumed that each different stimuli activate respective channels selective to their specific durations, hence by presenting multiple stimuli, these channels should be activated by both relevant and irrelevant stimuli. The question arises about whether these parallel activations might interact, and if so, what determines this interaction. Our findings suggest that the duration of distractors was integrated into the perceived target duration, as they varied systematically. Furthermore, our model was able to predict not only the combination of these two pieces of information as a source of bias, but also to consider that this interaction was modulated by the difference between both durations. Moreover, we were able to calculate the rate of this modulation as a decay parameter or leaking factor, which determined the weight of distractor durations in the final target estimation.

In this sense, we found a considerable variability in leaking factor levels among participants. While some of them were very good at ignoring distractors and did not bias their estimations unless the durations were very similar, others allowed distractor durations to influence their judgments significantly. We should consider that this variability in leaking factors might appear not only between observers but also within the same observer under different conditions. One possible reason for this sensitivity to external information could be task uncertainty. Participants were asked to detect differences that were actually non-existent but instead induced by unattended external stimulation. This possibly led to different levels of reliance on surrounding stimuli and therefore varying degrees of uncertainty that manifested through greater and more persistent biases.

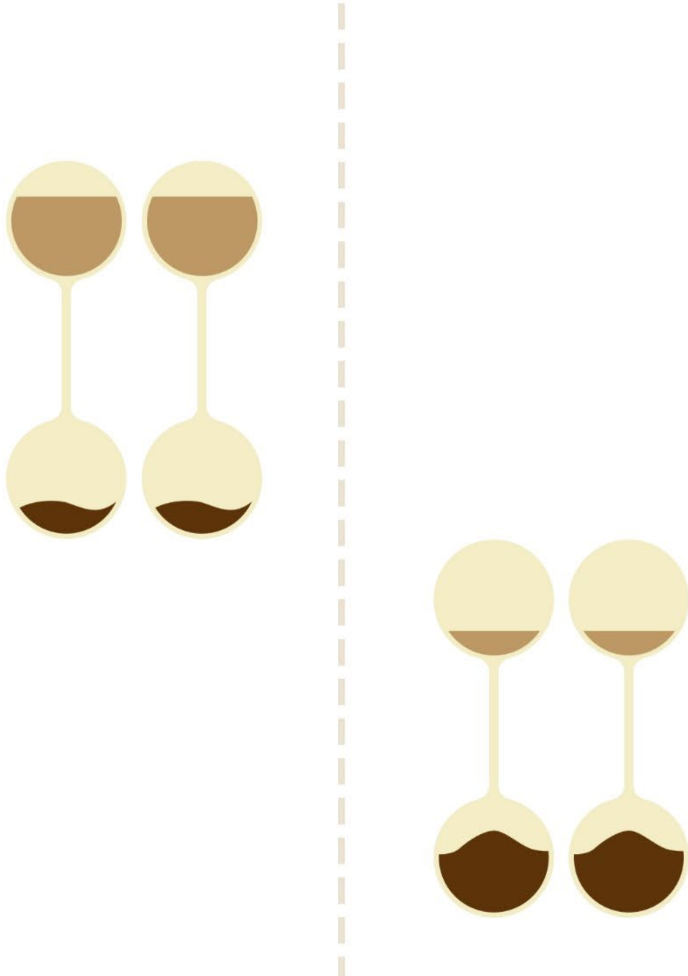
Being able to estimate the leaking factor parameter not only helps us better understand the perceptual process of duration of complex events but also could be useful for timing research itself, as it allows us to determine the range of durations used when studying temporal context effects. Additionally, applying it to different paradigms such as reproduction tasks could help in the discussion of the underlying nature of these effects, whether perceptual or decisional, and help clarify the sources of bias in multiple timing.

Finally, we explored whether individuals' capacity to discriminate between durations could influence the magnitude of the temporal context effect. We anticipated that participants with better discriminability should suffer less influence from distractors (measured by the leaking factor). Contrary to our expectations, we found a trend that, although not significant, suggests that better discriminability preservation when events were composed of multiple stimuli was in turn associated with greater leaking factor values. To our understanding, this links the capacity to extract information from a greater range of simultaneous sources with an increased sensitivity to noise from concurrent and irrelevant sources. Also, it could explain that the leaking of information between channels does not only describe how distractors interfere with our perceptual process but also points out an underlying feature of how humans integrate time information from multiple and more varied sources, even unattended ones.

CONCLUSION

Multiple timing is a critical aspect of how we experience time in the real world, where events rarely occur in isolation. Our study demonstrates that duration judgments of a single event can be biased by the temporal context consisting of simultaneous but irrelevant distractors. Most participants exhibited a central tendency effect, where the judgment of target durations shifted towards a general average of all overlapped stimuli, regardless of their task relevance. In fewer cases, this effect was reversed, with judgments shifting away from the distractor durations.

To further understand our findings, we proposed a relatively simple model using a single parameter that allows us to predict the influence of distractors and their decay if they are too different to the target, highlighting the importance of temporal context and uncertainty in time estimation. This research provides an entry point for further investigation into the complexity of multiple timing, aiming to enhance our understanding of the cognitive processes that underly time perception in our daily lives.



Part IV

STUDY 2:

OPTIMAL SAMPLING OF THE TEMPORAL STRUCTURE IN A DYNAMIC ENVIRONMENT

ABSTRACT

In everyday situations, we often need to track multiple durations simultaneously, such as when cooking various dishes or monitoring traffic while driving. These scenarios demand a high level of temporal awareness and strategic time monitoring to optimize performance and safety. While previous research has highlighted the cognitive demands of time tracking, the mechanisms behind managing multiple concurrent durations remain less understood.

This study examines how individuals manage and integrate multiple time estimates to guide behaviour in dynamic environments. We designed a task simulating a driving situation where participants had to detect vehicles approaching unpredictably from either side while adapting to changes in the temporal structure of the task. Our results revealed that detection performance decreased when the temporal structure became more demanding, highlighting the cognitive challenges in such tasks. Participants showed a correct prioritization strategy in their monitoring based on the durations of the events, yet they did not optimally adjust in response to changes in the task's temporal structure.

Using an optimal observer model, we compared participants' behaviour to theoretically predicted patterns. The model accurately predicted detection rates, suggesting that while participants could learn and use temporal regularities, their adaptations were suboptimal.

Our findings underscore the significant role of uncertainty and cognitive costs in complex time-based monitoring tasks. This research advances our understanding of strategic time monitoring and provides a basis for improving models of time perception and decision-making under dynamic conditions.

INTRODUCTION

Considering the findings of the previous study, where multiple timing effects are manifested in simple laboratory tasks, we decided to step forward towards more complex scenarios, closer to our daily life, where multiple timing plays a crucial role.

Sometimes, the effects of multiple timing not only influence how we perceive or judge the duration of events but also play a key role in how we actively track them and guide our behaviour based on these estimates. In other words, while we might often track the duration of events as a natural response to our environment, there are specific situations where this tracking is a fundamental component of the task itself. In such cases, actively tracking multiple event durations, keeping them active in our mental space, and being able to work with them becomes not just a consequence of the situation but a requirement of the task.

Consider a situation where we need to keep track of multiple timers, such as when cooking a meal with several ingredients that require different cooking times. In many cases, we can easily manage this by checking the state of each event and acting accordingly. If one of the elaborations is ready, we remove it from the heat without worrying about whether the elapsed time has reached the expected cooking time already. In the end, monitoring the duration of each cooking elaboration is informative, but not necessary, since we can check at any point and rely on other sources of information beyond just the elapsed time to make a decision. However, some other situations might not allow us to get this glimpse of information altogether, and if we cannot access the state of all events at the same time but only one at a time, we might need to rely much more on the tracking of the different elapsed times. In such cases, the element of uncertainty is key, as it requires us to plan an efficient behaviour that can compensate for our lack of predictability.

This brings up a crucial decision: How long should I sample information from one event, and how long can I stay without sampling information from the other event? Furthermore, if I need to switch between sampling one event to the other, how should I distribute my monitoring time on each of them?

Imagine now that you are in a vehicle on the highway. For your own safety, you might want to be aware of any other vehicles trying to pass you from either side. To do so, you would have to check each side mirror to see whether anyone is coming from behind, but sampling this information from one location occludes the other, as we cannot look at both sides simultaneously. If we only focus on one side, we will likely miss vehicles from the other. Therefore, to maximize the probability of detecting any vehicle approaching from either side, we should find the best proportion of time to spend looking at each location or, better, the frequency at which we should switch from looking at one lane to the other.

With this, we find how time monitoring becomes an example of the critical importance of timing capacities to solve daily tasks. Specifically, it involves not only keeping track of time but also associating actions to perform at precise points. Laera et al. (2024) highlight the importance of time monitoring and how it can be both costly and cognitively demanding, as it requires continuous attentional resources. Similarly to what we proposed above, they define strategic time monitoring as a behaviour where individuals check the time more frequently as the target time approaches. This strategic approach allows individuals to optimize their monitoring efforts, focusing their attention on the events at which the need to act becomes imminent.

In this regard, Beck et al. (2014) highlight the importance of temporal and spatial predictability in improving response times and attention allocation. They argue that predictability can be incidentally learned through inter-trial relationships, leading to more efficient task performance without explicit cues. This suggests that even in unpredictable environments, individuals can optimize their behaviour by learning and utilizing temporal regularities (Beck et al., 2014). Similarly, Echeverria-Altuna et al. (2024) demonstrate that individuals can use temporal regularities to orient attention and make decisions even under high spatial and action uncertainty. They showed that goal-dependent strategies are crucial for optimizing performance, and highlight the flexibility in using temporal information to guide behaviour in uncertain environments, which further supports the idea that effective monitoring and decision-making relies heavily on the ability to adapt to temporal regularities of the task (Echeverria-Altuna et al., 2024). Hyafil et al. (2023) further highlight that temporal integration is a fundamental aspect of perceptual decision-making and that decisions rely on integrating sensory evidence over time, even in noisy environments.

In this sense, and going back to our example, if we cannot predict when other vehicles will appear and from which lane, finding this timing at which we must switch from looking from one side to the other might not be simple. The critical information that we will have to use to define this pattern will be the duration of how long each vehicle will be detectable, from the first moment it is visible to the moment it would reach us. If we know how long each vehicle takes to close this gap, we also know how much time we can neglect that location and still be able to switch back and detect the potential vehicle.

For example, if vehicles coming from our right take four seconds to reach us (from the first moment they are visible), we could spend almost four seconds looking at the opposite side and still have time to detect them by switching sides just before it's too late. In contrast, if vehicles from the other lane take twice as much time to reach us, we can probably look away double that time without missing it. With this reasoning, by knowing how long vehicles from each side would take to reach us (depending on the average speed of that lane), we could decide for how long to sample at each location. This generates a monitoring pattern that optimizes our probabilities of detecting any event with absolute uncertainty about the location and moment they will appear, but just knowing the duration of each of them.

As demonstrated by Hoppe and Rothkopf (2016), humans are able to adjust the timing of eye movements based on environmental regularities in this type of tasks. In their study, participants optimized their gaze strategies to two separate locations by learning the temporal regularities of the events from each location, even when these were unpredictable in terms of when or where they would appear. This sets evidence for the ability of the human visual system to integrate temporal information to control monitoring behaviour in a way that maximizes detection efficiency, even in noisy environments (Hoppe & Rothkopf, 2016; Hyafil et al., 2023).

However, depending on whether the tracking of the multiple durations could be performed as a unified task or as a combination of simultaneous efforts, this could affect how successful we are at solving it. Clarke and Hunt (2016) reported that humans often fail to adapt their strategies optimally when required to split resources between multiple tasks. Their research showed that even when the optimal strategy is clear and stable, participants failed to modify their behaviour to achieve the best outcomes. This suggests a broader issue in human decision-making where there is a tendency to adhere to suboptimal strategies despite changing task demands (Clarke & Hunt, 2016).

Another aspect to consider that becomes clear when we think of real-life examples of this issue is that switching from sampling one location to the other might not be negligible. For example, in the driving situation we presented, when switching sides, one might need a fraction of time to turn the head and direct the eyes to the other side mirror. If this fraction of time is not integrated into the total time that we can stay looking away, we would risk missing the event at the very moment we are switching. In this sense, Hoppe et al. (2016) also emphasize the importance of considering the intrinsic costs of gaze behaviour, such as the time and effort required to switch between locations. Their computational model demonstrates that accounting for these costs is necessary for approaching optimal performance by trading off event detection rates with the costs of the associated eye movements (Hoppe & Rothkopf, 2016). In this line, Laera et al. (2024) also emphasize the importance of understanding the costs associated with time monitoring. They described that these costs, which can include cognitive load, attentional resources, and even social or monetary penalties, can influence how and when individuals choose to check the time. For example, they found that when monitoring incurs a cost, such as monetary deductions, individuals tend to adopt more strategic but less frequent checking behaviours which again highlights the trade-off between the frequency of checks and the strategic timing of those checks is crucial for optimizing performance in time-based tasks (Laera et al., 2024).

With that, we see that in these kinds of monitoring situations where we have maximum uncertainty about when and where an event will occur, we can guide our behaviour based only on the temporal structure of these events. Therefore, it becomes critical to work with multiple duration estimates at the same time, such as the duration we have for detecting each event and the time lost related to our manoeuvrability.

In our study, we build upon these insights to investigate how participants manage multiple time estimates in a dynamic environment. By examining their strategic monitoring behaviours, we aim to understand the extent to which they can adapt their strategies to optimize performance.

To this aim, we designed a novel task that tries to simulate the driving situation discussed earlier, where participants must detect vehicles that could appear at any moment from either their left or right side.

Here it is especially important that these events, in our case the presence of an approaching vehicle, are totally unpredictable, as it compels participants to guide their behaviour only by learning and tracking simultaneously different durations.

In contrast to our previous study, where multiple timing was something that produced an interference, here it is a requirement to solve this task.

Additionally, we aimed to test whether participants can adapt their behaviour to changes in the temporal structure of the situation. Specifically, we investigated if participants, apart from finding an optimal prioritization of where to look based on the duration of the events, could also adjust the looking times when these durations or the time they need to switch between observing lanes changes.

Finally, to better understand the underlying mechanisms that drive successful time-based task performance and the factors that may lead to optimal or suboptimal adaptations, we built a model of an optimal observer that predicts how much time should be dedicated to monitoring each area before switching according only to the knowledge of the temporal variables involved.

Monitoring pattern

We defined the combination of looking times at each location as the monitoring pattern. Which is composed of the duration at which an observer stays sampling at the same location before switching to the other one.

This monitoring pattern can be broken down into different time segments that compose a stable cycle that repeats until the event occurrence. For simplicity, we will develop all our explanations and analysis considering two different and exclusive event locations, although it could be adapted to more. This cycle starts with an interval where the observer is looking at one location, the end of which depends on their decision to stop sampling there. Then, it is followed by the switch to the other location, which comprises an additional interval during which they do not get information from either lane. This switch also comprises an interval that depends on the observers' limitations to realizing this change from sampling one location to the other. Then, the interval looking at the alternate location takes place. This is also followed by another switch to the original location, which finalizes the cycle by setting it again at the initial point. The full monitoring cycle is illustrated in Figure 4.1.

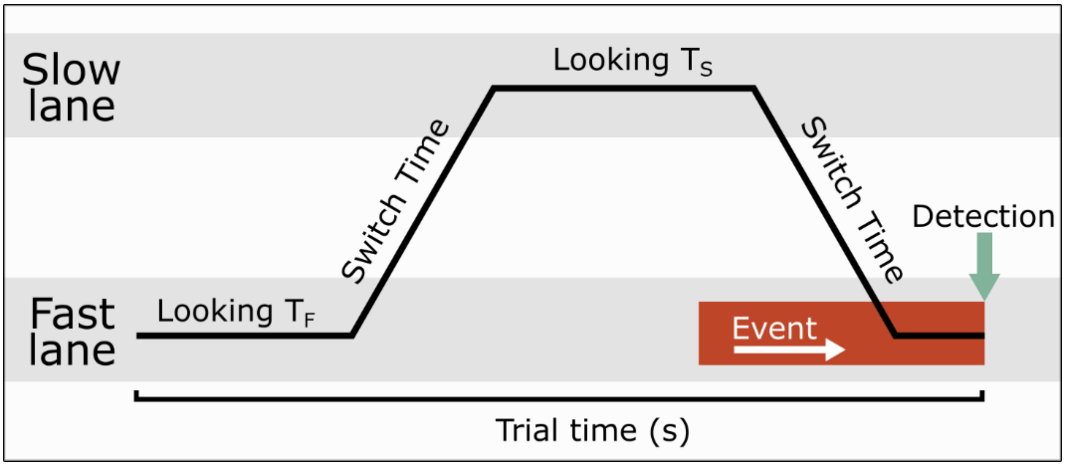


Figure 4.1. Example of a monitoring pattern cycle. The observer begins by sampling information from the fast lane for a duration denoted as T_F. The observer then decides to switch to the slow lane, during which time neither lane is visible, referred to as the switch time. Upon reaching the slow lane, the observer samples information for a duration denoted as T_S. Subsequently, the observer switches back to the fast lane. In this instance, an event occurs in the fast lane during the switch back, allowing the observer to detect it upon returning.

To mathematically formulate the cycle, we first define the total cycle time (T) as the sum of both looking times at each location (L_a and L_b) and the switch cost in time (SC) of going back and forth between them. Remember that looking times L_a and L_b are defined by the observer, whilst the switch cost is something imposed and thereby predefined.

$$T = L_a + L_b + 2 \cdot SC \qquad (4.1)$$

Then, we can calculate the probability of missing an event on each side (p_s) based on the total cycle time (T), the looking time at the opposite location ($L_{\bar{s}}$), the switch cost (SC), and the duration of that event (d_s). Simply put, it would be the proportion of the cycle time (T) where the duration of the event would be fully covered by the time looking at the opposite location and/or the time switching locations. Notice that, since the duration of the event could be long enough to exceed the combined looking time at the opposite location and both switching times, we capped the lower bound of the calculation at 0. This prevents negative probability results, which could occur mathematically if the event duration were larger than twice the switch cost plus the looking time to the opposite side.

$$p_s = \max\left(\frac{(2 \cdot SC + L_{\bar{s}} - d_s)}{T}, 0\right) \quad (4.2)$$

Finally, once we calculate both probabilities of missing each event for a given monitoring pattern, we can calculate the general probability of missing any event considering the event at each location equally probable.

$$p_{miss} = p_a \cdot 0.5 + p_b \cdot 0.5 \quad (4.3)$$

METHODS

Participants

The sample of the first consisted of twelve participants, 7 of them self-identified as female and 5 as male (mean age = 29, SD = 3.22). All of them had normal or corrected-to-normal vision and were naïve to the purpose of the experiment. The study is part of a research program that has been approved by the ethical committee of the University of Barcelona (IRB00003099) according to the principles stated in the Declaration of Helsinki. All participants gave written informed consent to participate in the experiment.

Apparatus and stimuli

The task was designed and conducted using Unity 2020.3.27f1 (*Unity 2020.3.27f1*, 2020). Stimuli were presented on a 24.5-inch ASUS ROG Swift PG258Q monitor with a resolution of 1920 × 1080 pixels at 240 Hz refresh rate. Participants were seated at approximately 57 cm from the screen.

Participants were presented with an overhead view of a red car that was 3 degrees wide and 6 degrees high, moving along a road across the vertical axis. The red car was always in a fixed position on the screen, centred horizontally and shifted vertically 3 deg towards the top of the screen. Grey cars (overtaking cars) of the same size could appear from the bottom of the screen, at 3.5 deg of eccentricity, and move towards the top at different speeds, depending on the speed condition and the lane at which they appeared. Three different pairs of speeds were used, where each lane had a different speed of 3 times greater than the other lane and was constant throughout the block. The location of the fast and slow lanes was determined randomly at each block, with values of 500 and 1500 ms, 750 and 2250 ms, or 1000 and 3000 ms at each lane respectively. For example, we could have one fast block where the left side was randomly selected to be the fast lane with a duration of 500 ms and the right side was therefore selected as the slow lane, where the duration would be 1500 ms. The onset of the overtaking cars was determined randomly on each trial following a uniform distribution between 3000 and 8000 ms. This was done to avoid predictability of the onset of the events and allow for enough time to record a monitoring pattern.

Half of the screen was always occluded, by darkening with a black layer of 0.75 alpha (opacity). See Figure 4.2 for a visual example of the task. At the beginning of each block, the top half of the screen was visible, and the bottom half was occluded, but as participants pressed the right or left keys the revealed area rotated to be oriented at the last pressed key's direction. Any area of the grey cars that overlapped with the occluded area became invisible. The speed at which this area completed a 180° rotation (which was always done passing from the top side) varied depending on the switch condition and could take 500, 750 or 1000 ms.

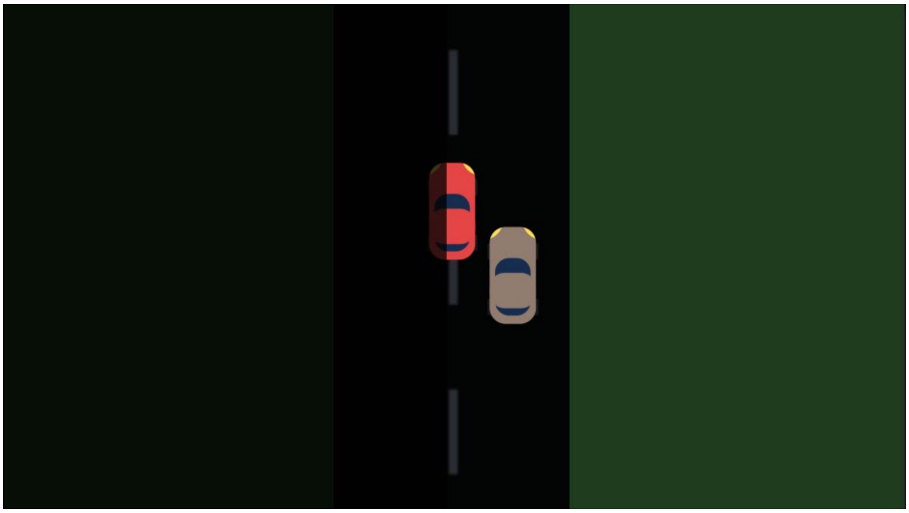


Figure 4.2. Screenshot of the task. The participant is revealing the right lane, where an overtaking car is approaching while the opposite lane is occluded.

Feedback

A green or red disk of 3 deg radius was presented at 10 deg above the vertical centre of the screen for 500 ms to provide feedback about the participant's response on each trial.

Procedure

Instructions

Participants were asked to imagine they were in the central red car, that other cars would try to pass them from either side and that their task was to press the spacebar key as soon as they could see them. They were informed that half of the screen would be occluded, and that overtaking cars in that area would not be visible, but that they could rotate this area to reveal either the left or the right side of the screen by pressing the left or right arrow keys respectively. In that regard, they were warned that this rotation could take some time and that they would not be able to switch again until the current rotation was completed.

Additionally, participants were informed that only one overtaking car could appear at a time, that it could appear with equal probability on either side and that the moment it would appear was determined randomly.

Configuration

All participants began the experimental session with a baseline block of 50 trials with a homogeneous event duration of 1500 ms at both lanes and a switch cost of 500 ms. They were also allowed for a short test of up to 5 trials to familiarize themselves with the task and controls prior to the baseline block.

We used 3 levels of duration/speed and 3 levels of switch time, combined in 9 experimental blocks. Every participant performed 50 blocks of each of these combinations of event durations and switch times. The order of the combinations was counterbalanced across participants, who were initially unaware of the temporal structure determined for each given block.

Measures

At each trial, we recorded the time at which participants produced every switch from looking one side to the other as well as the response time at which they pressed the detection key. This last response was then categorized under 3 possible scenarios.

- Hit: Participants pressed the space key while the car was being presented at the same lane they were looking at and before it reached them.
- False alarm: Participants pressed the space key but either the overtaking car had not yet appeared, or it was running through the occluded lane and participants were not directly seeing it.
- Miss: The overtaking car completed the full movement, reaching them without participants pressing the space key (expectedly due to running through the occluded lane).

We excluded the first 4 trials of each block, during which participants could identify the fast and slow lanes and calculate an approximation of each event duration and switch time.

We measured the number and type of responses for each participant during each block, as well as the looking time to each lane and the frequency of switching. These two later measures were used to define participants' monitoring patterns by calculating the average looking time to each lane on every block.

Feedback

Feedback was provided at the end of each trial. If participants detected the car on time (hit), a green disk was presented signalling a successful trial. In contrast, if a participant generated a false alarm or missed a car either from not pressing on time while looking at the appropriate lane or by looking for too long at the opposite lane, a red disk appeared that signalled a failed trial.

Optimality

We used the optimal observer model to predict the probability of detecting an event according to the participant's monitoring pattern at each block. This allowed us to assess how well the model predicts the observed proportion of detections from each participant and also to compare the monitoring pattern that they chose with the optimal pattern.

RESULTS

Performance

To check that participants were able to solve the task and detect the overtaking cars we calculated participants' proportion of detected cars at each lane for each combination of speed and switch cost.

We found that the percentage of detections of each participant varied across the different experimental conditions (see Figure 4.3). Overall, the number of detections decreased as the speed of the overtaking cars increased ($r(34) = -0.23$, $p = 0.019$ and $r(34) = -0.36$, $p < 0.001$ at fast and slow lanes respectively). The same happened with the switch cost, where longer switch times also correlated negatively with the percentage of detections ($r(34) = -0.63$, $p < 0.001$ and $r(34) = -0.85$, $p < 0.001$ at fast and slow lanes respectively).

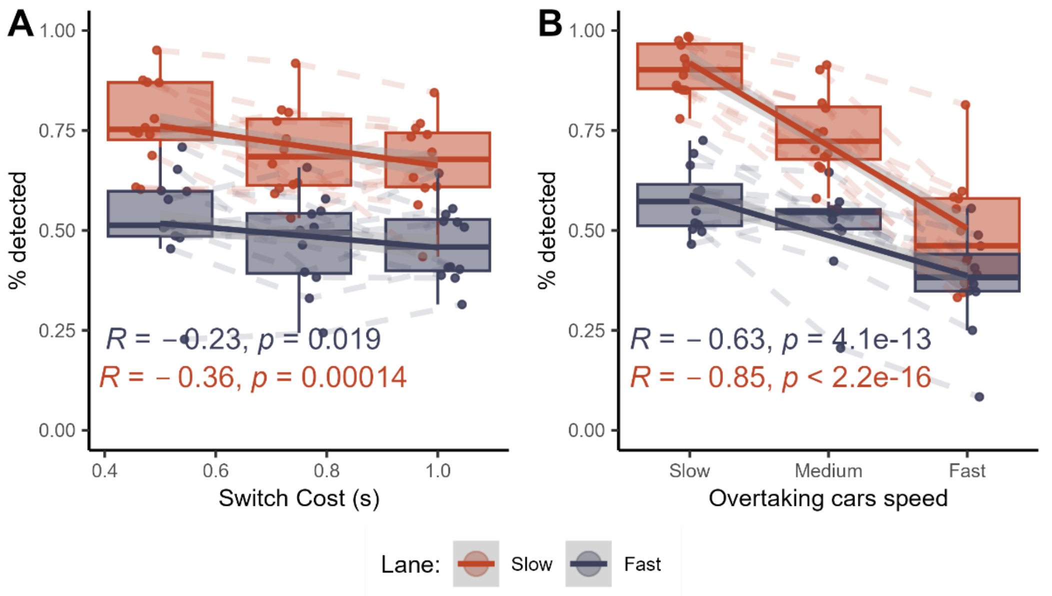


*Figure 4.3. Correlation between the percentage of detections and **(A)** Switch Cost or **(B)** Overtaking cars speed at slow and fast lanes.*

We also found a significant difference in the proportion of detected fast and slow cars in most conditions (see Figure 4.4). Specifically, with 500 ms switch cost, the detection of slow cars was significantly greater than the detection of fast cars at slow overtaking speed was slow ($t(22) = 5.87$, $p < 0.001$) and medium (t(22) = 3.69, p = 0.002). When switch cost was 750 ms, the detection of slow cars was significantly greater than the detection of fast cars at slow overtaking speed was slow (t(22) = 9.09, p < 0.001) and medium (t(22) = 3.5, p = 0.018). And 2hen switch cost was 1000 ms, the detection of slow cars was significantly greater than the detection of fast cars at slow overtaking speed was slow (t(22) = 7.92, p < 0.001) and medium (t(22) = 5.02, p < 0.001).

Overall, fast cars were harder to detect, but in general, participants were able to detect cars at both lanes in all conditions, and proportionally to the increased difficulty of conditions with increasing switch time or overtaking cars' speed.

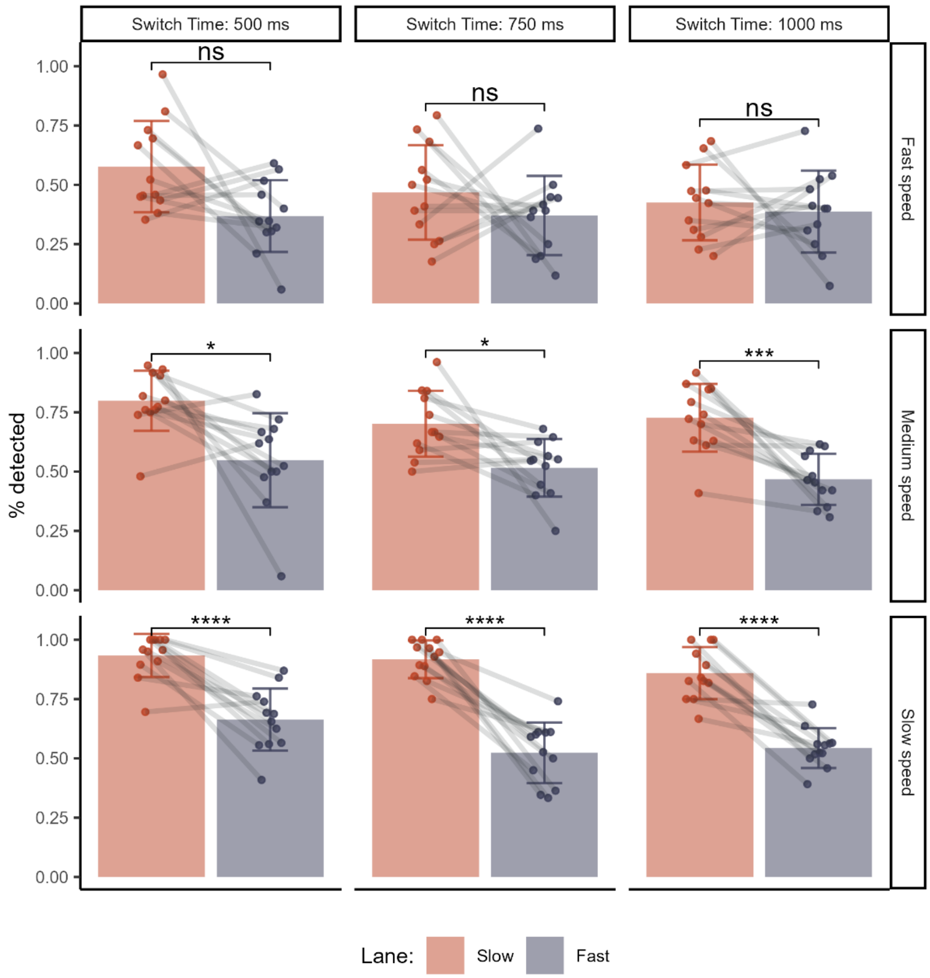


Figure 4.4. Comparison between the percentage of detections at the slow and fast lanes at each combination of Switch Cost and Overtaking cars speed.

Monitoring pattern

After confirming that participants were proficient in performing the task, we analysed their monitoring patterns to evaluate how they planned their behaviour to maximize car detection.

To reiterate, we define the monitoring pattern as the sequence of time segments that describe the average looking cycle, during which participants observe one lane, then shift to the opposite lane, and finally return to the initial lane. As previously described by (4.1, this pattern is characterized by the average looking time at each lane and the switch time between lanes.

First, participants should prioritize looking for longer times at the fast lane than the slow lane to increase their probability of detecting any overtaking car. To determine whether they followed this prioritization, we performed a paired t-test on the average looking times per lane from each participant. The results of the paired t-test indicated a significant difference in looking times between the fast and slow lanes, $t(11) = -6.47$, $p < 0.001$. The mean difference in looking times was 0.97 seconds, with a 95% confidence interval ranging from 0.64 to 1.29 seconds (see Figure 4.5A).

These results indicate that participants spent significantly more time looking at the fast lane rather than the slow lane, which shows a correct prioritization towards the area where events are harder to detect.

Changes from the temporal structure

To further investigate whether and how switch cost and general overtaking cars' speed would individually affect looking times at the fast and slow lanes, we conducted separate repeated measures ANOVAs for each lane.

Fast lane

The repeated measures ANOVA revealed a significant main effect of switch cost on looking time in the fast lane, $F(1, 11) = 6.34$, $p = 0.029$. However, there was no significant main effect of speed, $F(1, 11) = 0.55$, $p = 0.476$, and no significant interaction between switch cost and speed, $F(1, 11) = 0.12$, $p = 0.734$. This indicates that only the time required to switch lanes significantly affected how long participants looked at the fast lane. Specifically, the mean looking times to the fast lane were 0.959 s (SD = 0.857) for the 0.5 s switch cost, 1.27 s (SD = 1.26) for the 0.75 s switch cost, and 1.40 s (SD = 1.29) for the 1.0 s switch cost (see Figure 4.5B). This indicates that participants allocated more time to monitoring the fast lane when the cost of switching was higher, suggesting a conservative strategy to maximize detections at the fast lane under more constrained switching conditions.

Slow lane

The repeated measures ANOVA for the slow lane did not reveal any significant main effects of switch cost, $F(1, 11) = 1.85$, $p = 0.201$, or speed, $F(1, 11) = 3.22$, $p = 0.100$. The interaction between switch cost and speed was also not significant, $F(1, 11) = 0.31$, $p = 0.590$.

These findings are visually depicted in Figure 4.5B, illustrating the average looking times for every combination of switch cost and speed in the fast and slow lanes, respectively.

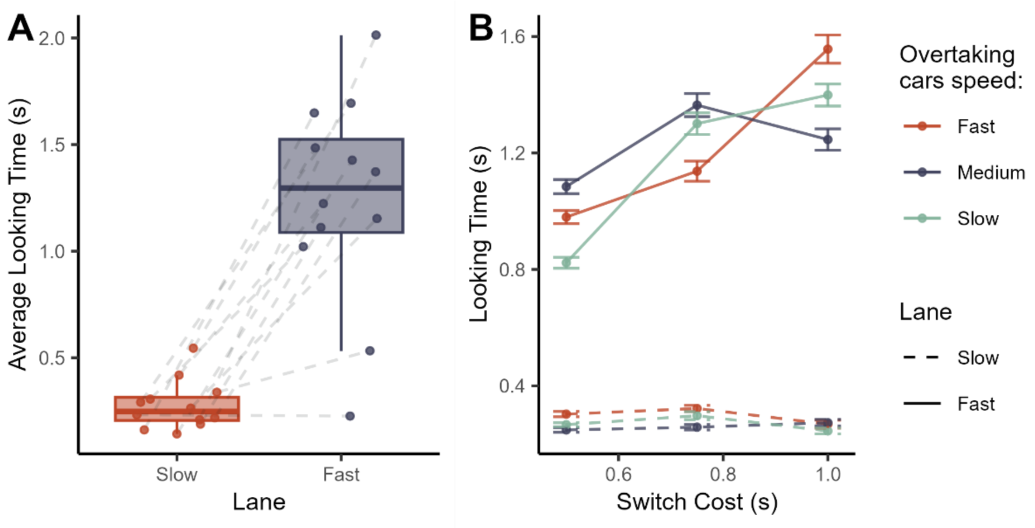


*Figure 4.5. Looking times **(A)** Distribution of average looking times from each participant at each lane. Participants prioritized looking for longer periods at the fast lane. **(B)** Variations of the grand average of looking times to changes in the temporal structure. Switch cost and overtaking cars speed increased looking times only at the fast lane.*

Optimality

The optimal observer model provides a theoretical framework for predicting the most efficient allocation of looking times under different conditions. By comparing the observed looking times with the optimal predictions, we can assess the extent to which participants' behaviour aligns with the model's predicted optimal pattern and identify any significant deviations.

To have a reference of how participants should adapt their looking times, we calculated the coefficients for the optimal looking times at the slow and fast lanes using the optimal observer model. These coefficients include the intercept, switch cost, overall speed, and their interaction. We then estimated the same coefficients for the observed looking times at each lane using a linear mixed-effects model (lmer), accounting for participants as a random effect. The observed coefficients were compared to the optimal coefficients by using their confidence intervals to obtain z-scores that determined whether they could be considered equal.

The analysis of the looking times to the slow lane revealed that the intercept was significantly higher than the optimal time ($z = 7.092$, $p < 0.001$). This indicates that participants stayed for a longer time (around 400ms) at the slow lane. Remember that in this case the optimal observer model expects the minimum looking time possible to the slow lane, but it is possible that participants needed this time to decide and process the action to switch back. In terms of the temporal context variables, neither the switch cost ($z = -1.576$, $p = 0.115$) nor the interaction between switch cost and overall speed ($z = 0.894$, $p = 0.371$) showed any differential effect between optimal and observed variations. The optimal model expects a near-zero effect of switch cost and overall speed since the least amount of looking time should be dedicated to the slow lane, regardless of these variables. However, participants showed a significantly different slope of speed ($z = -1.962$, $p = 0.049$), where they decreased their looking time as the overall durations also decreased.

Regarding the fast lane, we found suboptimal adjustments of looking times from every variable. Participants showed different effects from switch cost ($z = 9.463$, $p < 0.001$), overall speed ($z = 9.463$, $p < 0.001$), the interaction of both ($z = 6.008$, $p < 0.001$) and even the intercept ($z = 7.135$, $p < 0.001$) than those expected from an optimal observer. According to the model, the looking time to the fast lane should start at an initially lower value, then it should decrease as the switch cost increases and as the overall speed also increases. Basically, the more difficult the task gets due to the temporal constraints (by the switch cost) or the reduction in the duration of events (increased speed), the more frequently participants should switch to maximize the probabilities of detecting an event at any lane. We found that participants follow a more conservative strategy, where they dedicate longer looking times to the fast lane as the task gets more difficult, although in this way they substantially reduce their predicted probabilities of detecting a car in the slow lane. These differences between the optimal and observed monitoring patterns can be observed in Figure 4.6.

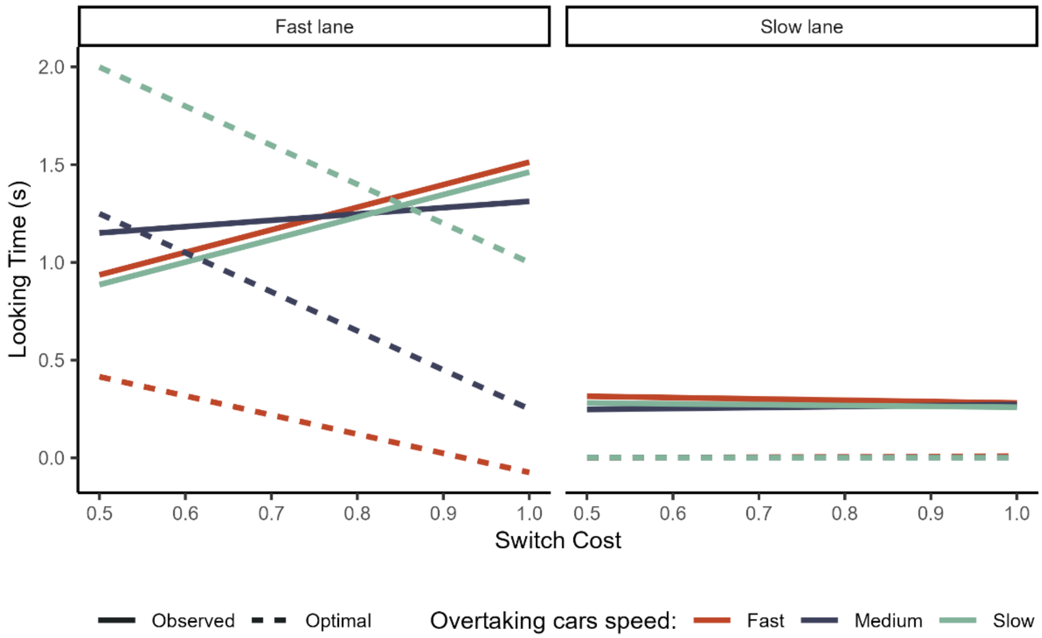


Figure 4.6. Linear functions of looking times obtained from the mixed-effects model at each combination of variables. Variations expected from an optimal observer are presented in dashed lines while observed data is presented with solid lines.

In summary, the analysis indicates that participants' monitoring patterns do not align well with the expected from an optimal observer according to our model. However, the significant discrepancies between observed and optimal coefficients suggest that participants might not be selecting an adequate monitoring pattern due to factors not accounted for in the model, such as risk perception, fatigue, or just a limitation in properly keeping track of the many different temporal properties of the environment and work with them to find an optimal solution.

Predictability

Although participants did not seem to follow the optimal model variations across switch cost and overall speed levels, this does not necessarily mean that the model does not hold. Participants could just be suboptimal in adapting their monitoring pattern, and the model could still be valid as a predictor of their performance. To test this, we assessed the model's predictive capacity under different conditions.

To assess the relationship between the observed and predicted detection proportions, we conducted a correlation analysis with the data from each participant at each condition. We found a strong positive correlation (r = 0.785, $t(106)$ = 13, p < 0.001) between the observed proportion of misses and predicted probabilities obtained from the model. To further explore this relationship, we performed a linear regression analysis that revealed a significant intercept value of 0.217 (SE = 0.019, p < 0.001) that signals a systematic bias where the observed proportions are constantly higher than the predicted ones and a significant slope coefficient of 0.829 (SE = 0.064, p < 0.001) that underscores a robust relationship between observed and predicted proportions of misses. The high significance of the slope confirms that the model captures the general trend and can reliably predict variations in the probability of miss based on the monitoring pattern. Overall, the results indicate that while there is a tendency to underestimate the proportion of misses, the model's predictions are proportionally accurate. Figure 4.7 illustrates this relationship between observed and predicted detection proportions.

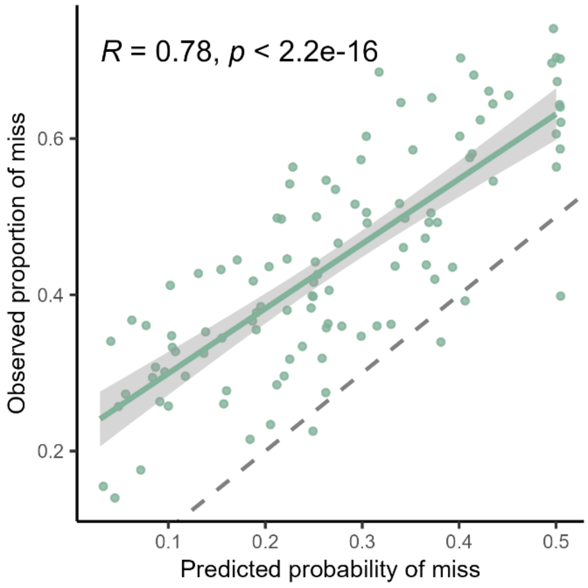


Figure 4.7. Correlation between observed and predicted detection proportions from the optimal observer model. The identity line (dashed) represents perfect prediction from the model.

DISCUSSION

The present study aimed to explore the capacity of observers to maintain, keep track of, and integrate multiple duration estimates simultaneously to guide their behaviour optimally in a dynamic environment. We designed a novel task simulating a driving situation where participants had to detect vehicles appearing unpredictably from either side. Our results provide valuable insights into the strategic monitoring behaviours of participants and how optimally they adapt these strategies based on the temporal structure of the task.

Our findings reveal that participants' detection performance varied significantly across different experimental conditions, influenced by the speed of the overtaking cars and the switch cost. Specifically, detection rates decreased as the speed of the cars increased and as the switch cost became longer. These results align with previous research by Laera et al. (2024), who highlighted the cognitive demands and costs associated with time monitoring. Our study extends these findings by demonstrating how these costs impact the ability to track multiple intervals and make timely decisions in a dynamic environment, especially in the most difficult conditions.

Participants showed a tendency to prioritize the fast lane over the slow lane by spending significantly more time looking at the former. This behaviour indicates a correct prioritization strategy, as detecting faster-moving cars is inherently more challenging, and an optimal monitoring pattern is determined by dedicating as little time as possible to the slow lane and adjusting the looking time to the fast lane in relation to the slow cars' duration. However, our analysis also revealed that participants did not optimally adjust their looking times in response to changes in the temporal structure, defined by the switch cost and the overall speed of the cars. While the optimal observer model predicted that participants should decrease their looking time as the task difficulty increased, participants instead adopted a more conservative strategy, dedicating longer looking times to the fast lane. This conservative approach reduced the probability of detecting cars in the slow lane in exchange for ensuring detections in the fast lane, suggesting a suboptimal adaptation to the task demands.

Our results support the broader notion that human decision-making often struggles with achieving optimal outcomes under conditions of divided attention and varying task demands (Clarke & Hunt, 2016). In their study, Clarke and Hunt (2016) argued that the suboptimal selection of behaviour may not stem from poor prioritization of task accuracy, but rather from a decisional bias that steers behaviour away from strategies perceived as overly influenced by chance. In their study, participant preferred to focus on a strategy that, although did not maximize their probability of success, was associated with a greater level of agency, in contrast to other strategies where the outcome was perceived as being more dependent on chance.

This could be analogous to our results. As the task became more difficult with increased switch time, participants prioritized looking at the faster lane (where the events are harder to detect). This could have been to avoid missing the target while switching. They stayed for a longer time at the fast lane and switched less, leaving less weight to the uncertainty about where the event would start, and giving more weight to the possibility that the event would appear at that lane.

These results highlight the struggle to reduce the impact that uncertainty has on our behaviour selection. In a task where events were unpredictable and the optimal solution would be found by calculations on its temporal structure, participants demonstrated that they could gather and maintain the mental representations of both event durations, but when the task demands changed, they sought to reduce the temporal uncertainty about the onset of these events, even in a suboptimal way.

The observed discrepancies between participants' behaviour and the optimal observer could be attributed to several factors. One possibility is that participants' risk perception influenced their monitoring patterns, leading them to adopt safer but less efficient strategies. Also, as we mentioned above, the cognitive load associated with keeping track of multiple temporal properties may have hindered their ability to find an optimal solution. This aligns with the findings from Beck et al. (2014), who emphasized the importance of predictability in improving task performance. Even in unpredictable environments such as our task, individuals can technically optimize their behaviour by learning and utilizing temporal regularities. However, our results suggest that participants may struggle to fully capture these regularities when faced with high cognitive demands.

Along the same line, our findings support the notion that perceptual decision-making relies on integrating sensory evidence over time, even in noisy environments (Hyafil et al., 2023), as participants had to integrate information about the durations of potential events and the costs associated with switching their attention. However, the suboptimal adaptations observed in our study suggest that while participants can integrate temporal information, they may not always do so in a manner that maximizes performance. Moreover, the inherent uncertainty in when and where the events would occur likely exacerbated the difficulty in maintaining optimal performance, underscoring the significant role of uncertainty in timing tasks.

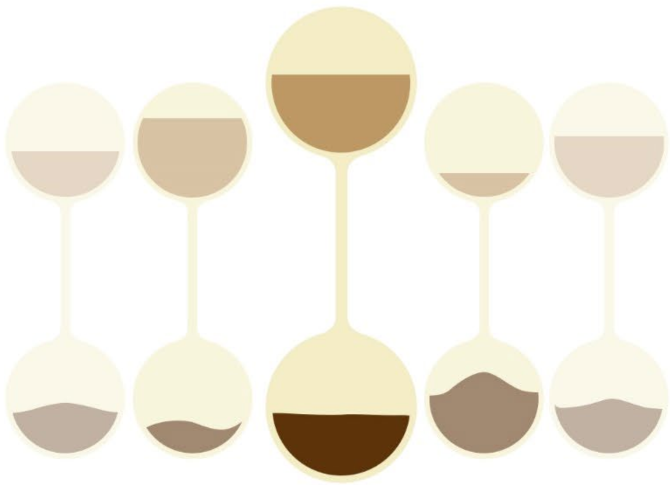
The increase in difficulty is especially relevant in relation to the costs associated with time monitoring, which play a significant role in shaping participants' behaviour (Laera et al., 2024). When monitoring incurs a cost, individuals tend to adopt more strategic but less frequent checking behaviours. Our study corroborates this by showing that participants adjusted their monitoring patterns based on the switch cost, though not always in an optimal way. The trade-off between the frequency of checks and the strategic timing of those checks is crucial for optimizing performance in time-based tasks.

On another note, despite the observed suboptimal behaviour, our optimal observer model showed a strong correlation with the actual detection rates, indicating that the model can reliably predict the probabilities of missing an unpredictable event based only on the monitoring pattern. This suggests that while participants may not perfectly adapt their behaviour to changing conditions, the general trend of their performance aligns with the model's predictions. However, the systematic bias observed where observed misses were higher than predicted highlights that there is still room for improving the model. It is possible that exploring additional components related to participants' states, such as the fatigue associated with continuous changes, or the biases associated with risk aversion could help us better understand how these monitoring patterns are finally determined. Additionally, the element of uncertainty in both the timing and location of events plays a critical role here, as it directly impacts the participants' ability to align their behaviour with the optimal model. This emphasizes the need to further explore how the degree of uncertainty about each time estimate influences how much weight these timing properties are given in the establishment of monitoring strategies.

With this, we find that even when participants have the necessary information available to solve a task and find stable strategies, uncertainty often leads to suboptimal decisions. This is particularly relevant in the context of time perception and the monitoring of multiple intervals, where uncertainty can severely impact decision-making and strategy selection. When individuals are unsure about their ability to accurately perceive and estimate time intervals, or when the task demands are ambiguous, they are less likely to allocate their attention and cognitive resources efficiently. This misallocation can result in increased errors and variability in time estimation, highlighting the importance of addressing uncertainty when interpreting timing behaviour. By understanding the role of uncertainty, researchers can better design experiments and interpret data, ultimately leading to more accurate models of how humans perceive and manage time.

CONCLUSION

In conclusion, our study provides important insights into how individuals manage multiple time intervals to define strategic monitoring behaviours when tasked with detecting unpredictable events. While participants demonstrated an ability to integrate temporal information and prioritize more challenging tasks, their adaptations were not always optimal. The findings underscore the cognitive demands and costs associated with time monitoring and the challenges in achieving optimal performance under dynamic conditions.



Part V

STUDY 3:

MEASURING UNCERTAINTY WITH A MODIFIED REPRODUCTION TASK

ABSTRACT

Estimating durations is often challenged by inherent uncertainty. Traditional approaches have focused on measuring perceived time directly but have struggled to quantify the associated uncertainty effectively. Our study explored the potential of the bracket method as a direct measure of this uncertainty. In the task, participants were asked to indicate a range within which they believe an interval ends, providing a more nuanced measure of temporal uncertainty.

We compared the bracket method to the traditional discrete reproduction method across intervals of 0.6 to 4 seconds. Results showed high consistency between the methods in accuracy and precision, validating the bracket method as an effective alternative.

Furthermore, the bracket method provided significant insights into the nature of uncertainty in time perception. We found that the length of the bracket increased with the duration of the interval, aligning with the scalar property of timing. This suggests that the bracket method not only matches the discrete method in terms of basic performance metrics but also offers a direct measure of perceptual uncertainty.

Analysis of the variances in start and stop times of the bracket indicated contributions of both additive and multiplicative noise components in the timing process. These findings provide a deeper understanding of the cognitive mechanisms involved in time perception, particularly how noise influences the accumulation of perceived time.

Published as:

Boned, J., & López-Moliner, J. (2024). Quantifying uncertainty in time perception: A modified reproduction method *i-Perception, 15*(0), 1–18. https://doi.org/10.1177/20416695241279675

INTRODUCTION

The previous studies highlighted that time perception is a complex and cognitive process that is constantly faced with many challenges. As detailed in the general introduction, our ability to measure time is influenced by various internal and external factors (Kanai et al., 2006; Matthews & Meck, 2016; Vatakis et al., 2018; J. Wearden, 2016), leading to a significant role of uncertainty in our time estimates. This uncertainty can impact our duration judgment and decision-making processes, as well as deviate our time estimates, which makes it a critical area of study in time perception research.

Several methods that were described in the general introduction have been employed to measure this uncertainty, each with its own advantages and limitations. Traditional approaches, such as calculating the variability of estimates in quantitative tasks or obtaining psychometric functions, provide useful insights but also present significant caveats. These methods often deliver a global measure of uncertainty for the entire task, failing to capture the uncertainty associated with individual responses. Moreover, methods that rely on metacognitive judgments (Akdoğan & Balcı, 2017; Corcoran et al., 2018; Cropper et al., 2024; Jovanovic et al., 2023; Lamotte et al., 2017) can be influenced by higher cognitive functions and external biases, potentially obscuring the very uncertainty they aim to measure.

In an effort to overcome these limitations, we propose using a modified reproduction task called the "Bracket method," which builds on the promising yet underused start-stop procedure (Kladopoulos et al., 1998). The Bracket method involves participants bracketing their duration estimates with a range, providing a direct measure of uncertainty on a single-trial basis. Instead of asking them to reproduce by delivering a discrete response at the exact moment the interval would finish, they are asked to first start a continuous response as soon as they believe it possible that the interval to be reproduced has ended (start time), hold it, and stop the response as soon as they are sure that the interval to be reproduced has already ended (stop time) (see Figure 5.1 for a visual representation of this type of response). This approach addresses several key issues associated with traditional methods: it does not require metacognitive evaluations, provides a more objective measure of uncertainty that is integrated with the time estimate itself, and does not require any

S3

additional response from participants, minimizing task duration and participant fatigue. Moreover, it allows for the estimation of both the point of subjective equality (PSE) and the difference limen (DL) on a single-trial basis (Kladopoulos et al., 1998), which can serve as measures of accuracy and uncertainty, respectively.

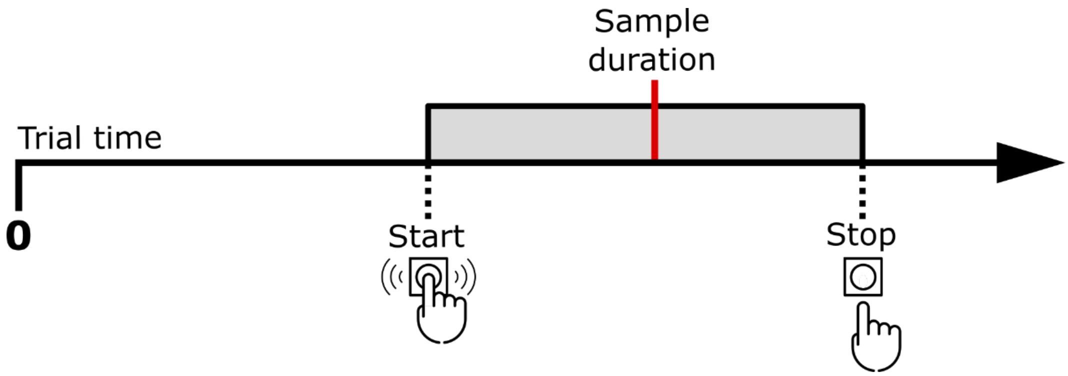


Figure 5.1. Example of a reproduction response under the start-stop procedure. The first response after interval onset determines the start time and the ending of this response determines the stop time.

Building on this foundation, the primary objective of this study is to compare the Bracket method with the traditional reproduction method in terms of their ability to measure time perception. These two methods have not yet been tested against each other; however, we hypothesize that the Bracket method will provide duration estimates equivalent to those obtained with the traditional method. Additionally, we aim to assess whether the additional measures obtained from the Bracket method can be used to reliably quantify uncertainty and be useful in addressing the nature of noise under uncertainty in time estimates through this new method.

Bracket as a threshold proxy

In contrast to the traditional reproduction method, the bracket method delivers us two time points that should be interpreted differently from the traditional reproduction time. To understand what each of these measures represents at a cognitive level, we must first delve into the perceptual decision process that involves the timing of an interval.

In timing tasks such as those presented in the present thesis, participants generate prospective estimates by engaging in a continuous process of comparing the subjective elapsed time (how long it feels since the event started) with a mental representation of the duration they are comparing it to (a duration criterion). As time goes by, the discrepancy between these two values decreases as the subjective elapsed time grows closer to the reference time. When this discrepancy diminishes enough, it reaches a perceptual threshold, after which both durations are perceived as equal. However, if time continues beyond this point, the discrepancy increases again and eventually reaches another threshold, making them distinguishable once more (Gibbon & Church, 1990; Kladopoulos et al., 1998). This process underscores that, to accurately compare two durations, we not only have to do a proper tracking of the elapsed time and keep a stable representation of the target interval but also need to have precise thresholds that delimit enough the range within which these two intervals are matched.

This raises the question about how these thresholds are established. They are directly related to the sensibility that can be different for each participant and are also influenced by uncertainty, as it can make durations inherently harder to discriminate, but aside from individual differences or situational factors, we can discuss how other more predictable aspects can also affect the distance between these thresholds, such as the magnitude of the stimuli.

According to Gibbon and Church (1990), the discrepancy between subjective and remembered time needed to discriminate them is proportional to the remembered time. This means that thresholds diverge further as the target duration increases. This aligns well with the traditional claim of the scalar property of timing and is associated with a multiplicative type of noise. However, if we conceive the scalar property of timing as a form of Weber's Law, there could still be multiple combinations of noise and transducer (the representation of the relationship between real and perceived duration), that could still hold with this law (Zhou et al., 2024). For example, a transducer that follows a power function with an exponent smaller than 1 would still comply with Weber's Law if additive noise is present (Zhou et al., 2024) (see Figure 5.2 for different examples of adherence to Weber's law with each type of noise). Therefore, to discuss the compliance with the scalar property, we should consider both the transducer and the shape of the noise, which should in turn determine these thresholds.

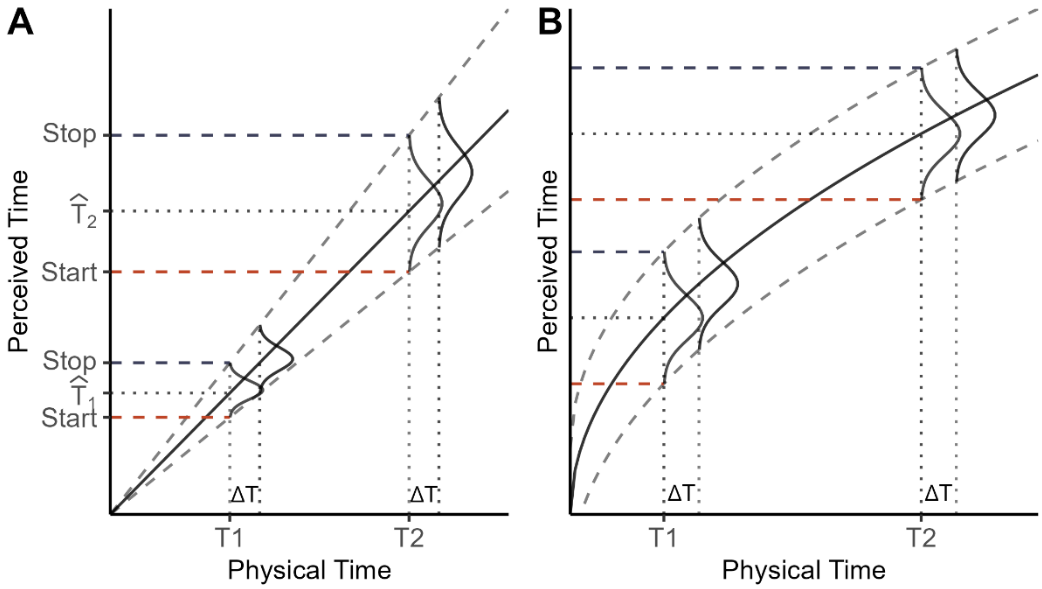


Figure 5.2. Increase in threshold range (dashed lines) in relation to the transducer (solid lines). The start and stop boundaries of the bracket (blue and red lines respectively) represent a proxy for this range. ***(A)*** *Example of multiplicative noise. The same increase in physical magnitude (ΔT) at T1 and T2 is harder to discriminate at longer durations (T2) due to the increase in noise.* ***(B)*** *Example of additive noise (independent of magnitude). The power function transducer makes the same increase in magnitude (ΔT) harder to discriminate at longer durations but this time due to the compression of the transducer.*

In our study, we conceptualize the bracket length as a direct measure of the temporal window within the two thresholds, with the start and stop times indicating when each of them is reached. We believe that by analysing how the start and stop times and the length of the bracket vary across the different target durations, we could not only reinforce the correspondence of these behavioural measures as proxies for the perceptual decision thresholds but also this could help us assess the nature of the process noise that determines them. In this regard, we are initially open to the possibility of the relation between noise and stimulus magnitude being either additive, multiplicative, or a combination of both, and expect the bracket method to be a useful tool to elucidate between these possibilities.

To assess this, we propose a definition of the bracket that will allow us to later address the nature of the noise that determines the threshold range:

$$\boldsymbol{Bracket} = \boldsymbol{c_a} + \boldsymbol{c_m} \cdot \hat{\boldsymbol{t}} \qquad (5.1)$$

Here, the bracket depends on the contribution of two types of components.

- And **additive** component (c_a) that remains constant across target durations. It represents the minimum difference that participants need to distinguish between them and is independent of stimulus magnitude.
- A **multiplicative** component (c_m) that increases proportionally to the perceived duration ($\hat{t}$).

If the bracket length indeed relates to the distance between thresholds, we have different ways to assess the nature of the underlying noise by analysing different aspects of the bracket.

Looking at bracket length

If brackets are solely determined by an additive component, they should remain constant across durations, with start and stop times always being placed at a constant distance between them.

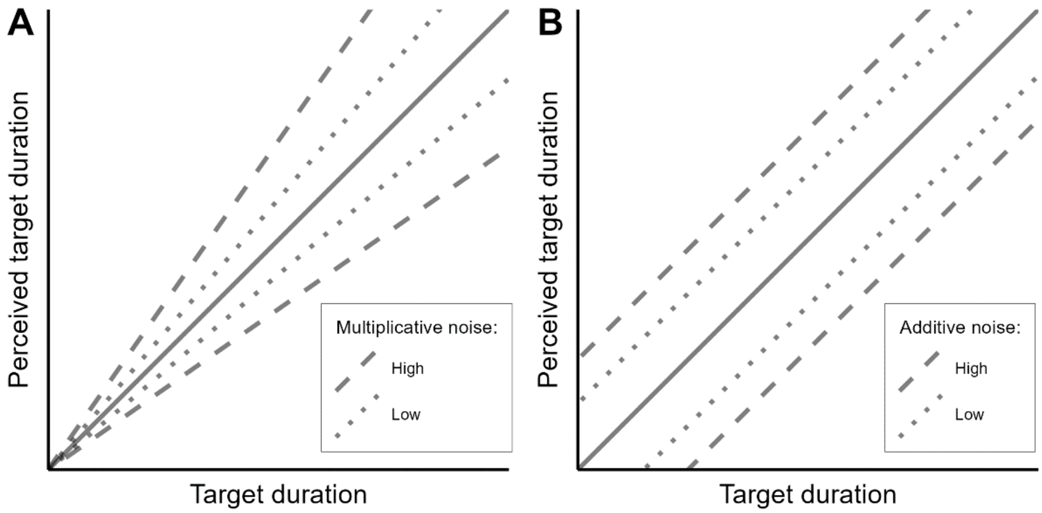


Figure 5.3. Solid lines represent a linear transducer of how the perceived duration represents real duration. Dashed and solid lines represent the spread of perceived times due to different sources of noise. ***(A)*** *Multiplicative noise correlates with the magnitude of the stimuli. Increasing variability at longer durations.* ***(B)*** *Additive noise is independent of stimulus magnitude and is stable across the range of durations.*

Conversely, the presence of a multiplicative component would result in a systematic relationship between perceived duration and bracket length, where the distance between start and stop times would increase along with the magnitude of duration. See Figure 5.3 for an example of different contribution levels of these components to the start and stop range.

Looking at start and stop times variability

Another approach to assess the nature of noise in the establishment of the perceptual thresholds that benefits from the bracket method is to explore how the variances of start and stop times evolve through time. According to pulse-accumulation and ramping activity models, each pulse of the internal clock, each accumulation of evidence, is subject to some degree of noise which in time estimation is translated to some variability in the accumulation of perceived time per unit of physical time (Gibbon & Church, 1990; Simen et al., 2016). Because of this inherent variability, since more noise can be accumulated as time advances, we hypothesize that stop times should exhibit greater variability start times due to the accumulation of more pulses and potentially more instances of noise. Even more interestingly, the relative difference in variability between the two moments could also help us disentangle the nature of noise.

For example, if the distance between start and stop times remains invariant across different target durations (indicating a purely additive nature), the relative variability between these two points would decrease as durations increase. This occurs because a larger proportion of the total variability would be shared by both points, given that there is more time to accumulate noise before reaching either point than during the interval between them. When the distance between start and stop times is constant (additive nature), the absolute difference in variability stays roughly the same, but the accumulated noise makes the relative difference much smaller as the variabilities of the start and stop times become more similar. Therefore, by obtaining the ratio of the variance of stop times to the variance of start times, we could identify a purely additive nature of noise. This would be indicated by the ratios tending towards an asymptote of 1 (equality of variances) as target durations increase. The strength of this additive component would determine how long the difference between variances persists before dramatically falling to this asymptote and becoming negligible.

On the other hand, multiplicative noise could also be detected with this approach. According to Weber's law (a form of the scalar property), if we assume a linear increase between perceived and physical time, we should also find an increase in estimated variability as the magnitude increases. This could be observed by the spreading of the bracket, as longer durations are more difficult to discriminate, the start times will be reached sooner, and the stop time will be postponed to a later time. This would also influence the ratio of variances of stop by start times. Specifically, we would find that as durations increase, the variance of stop times would increase more than the variance of start times. This in turn would produce a higher value of the ratio of variances, which although also decreasing in the long term, would tend to an asymptote greater than 1.

In the case of a combination of additive and multiplicative components, we just need to combine these properties that we mentioned. We would expect to find ratios of variances tending to an asymptote determined by the multiplicative component (greater values of the asymptote related to greater contribution of this component) and with a decaying rate that would depend on the contribution of the additive component (reaching faster the asymptote with smaller levels of the additive component). Figure 5.4 illustrates different examples of the ratio of variances as durations increase with different contributions of each component.

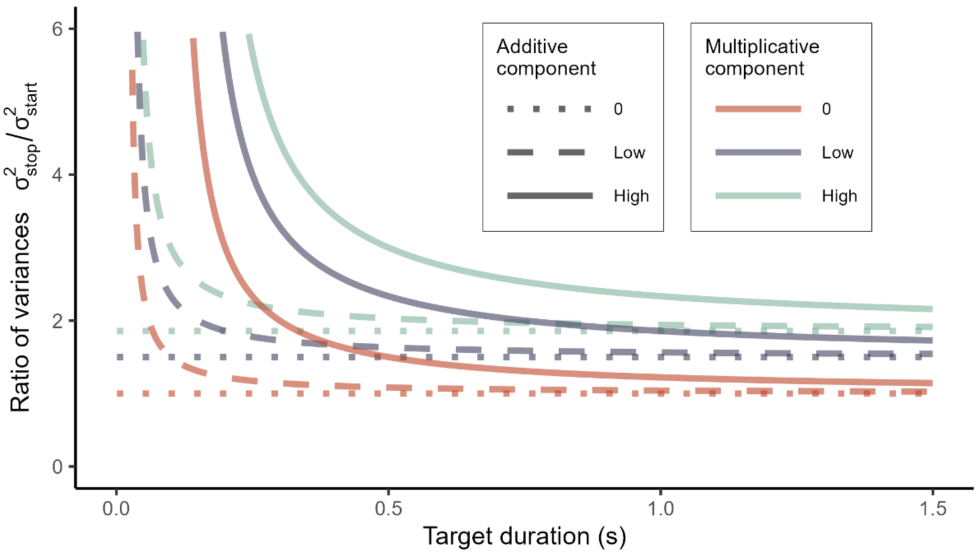


Figure 5.4. Simulations of the ratio of variances with different levels of additive and multiplicative noise components. The rightward asymptote is mostly determined by the multiplicative component and the approximation to this asymptote is modulated by the additive component.

Finally, a model such as the one we propose in Equation (5.1 could also account for both noise types. By combining the properties that we described, depending on the contribution of each type of noise we could find that the additive component could be calculated by how fast the variances ratio decays to the asymptote while the multiplicative component would determine the height of this asymptote.

METHODS

Participants

The sample of this study consisted of fourteen participants, 6 of them self-identified as female and 8 as male (mean age = 28.36, SD = 4.38). All of them had normal or corrected-to-normal vision and were naïve to the purpose of the experiment. The study is part of a research program that has been approved by the ethical committee of the University of Barcelona (IRB00003099) according to the principles stated in the Declaration of Helsinki. All participants gave written informed consent to participate in the experiment.

Apparatus and stimuli

The task was designed and conducted using Unity (*Unity 2020.3.27f1*, 2020). Stimuli were presented on a 24.5-inch ASUS ROG Swift PG258Q monitor with a resolution of 1920 × 1080 pixels at 240 Hz refresh rate. Participants were seated at 57 cm from the screen.

The visual stimuli consisted of white or red disks with a diameter of 3 deg and a white cross of 2 deg presented against a grey background.

Procedure

During the experiment, regardless of the condition block, each trial consisted of two distinct phases: a learning phase and a reproduction phase. In the learning phase, participants measured an interval presented through visual stimuli. In the reproduction phase, they delivered an estimate of that same duration.

The task was self-paced, meaning that the learning phase would not start until participants' input. In this way, participants could take short rests if needed during the block, although were warned to not abuse of these rests.

Learning Phase: Initially, a white cross (2 deg) was displayed at the centre of the screen and remained until participants pressed the CTRL key, prompting its disappearance. Following a 1500 ms delay, a white disk (3 deg in diameter) was presented for 200 ms at a random position within a 12x12 deg area centred on the screen. After a variable interval matching each trial's target duration, a red disk (3 deg in diameter) appeared at the same location for 200 ms. Participants were instructed to focus on the interval between the two stimuli.

Reproduction Phase: After a 1500 ms delay following the red disk's disappearance, the white disk reappeared at a new random location within the same area for 200 ms, indicating the start of the reproduction phase. Participants were required to estimate the time at which the red disk should appear again according to the same interval they were just presented within the learning phase. The end of this phase was marked by the participant's response, which varied depending on the reproduction method used in that block (either discrete or bracket reproduction, as presented in Figure 5.5).

- **Discrete Reproduction Blocks**: Participants pressed the SPACE key at the exact moment they estimated the red disk should reappear, mirroring the interval from the learning phase. Therefore, their response should be timed with the expected appearance of the red disk.
- **Bracket Reproduction Blocks**: Participants were instructed to press and hold the SPACE key as soon as they anticipated the red disk's appearance and release it when they were certain it would have already appeared, following the interval from the learning phase. They were also encouraged to keep the press duration as short as possible while ensuring it encompassed the target duration's end. Here, instead of synchronizing their response to the offset of the interval, they should behaviourally generate a sort of confidence interval that surrounds that same offset.

In both cases, they were warned that the red disk would not appear again during the reproduction phase and that they should time their responses according to the prediction they made about when it was going to appear, basing this prediction on the interval presented at the learning phase.

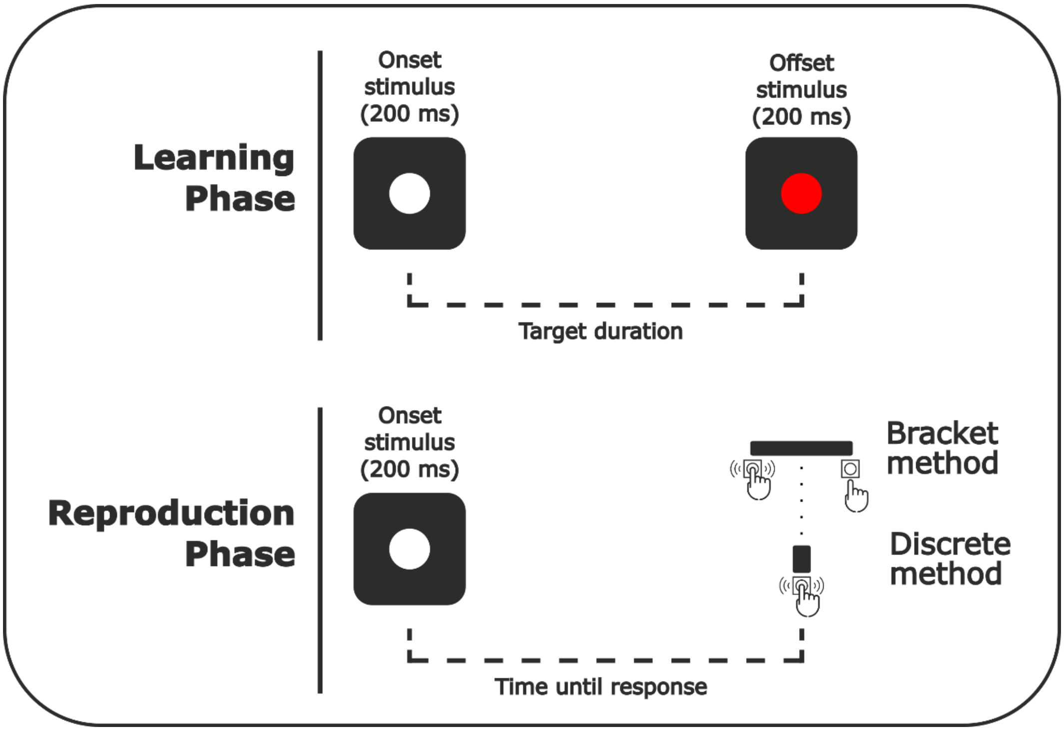


Figure 5.5. Visual example of the reproduction task sequence. The target interval was presented once through the learning phase and then reproduced during the reproduction phase. The reproduction ended at key press onset during the discrete reproduction blocks and at the key press offset during the bracket reproduction blocks.

To mitigate potential spatial adaptation effects, the location of stimuli in both phases was randomized so that the onset stimuli (white disks) were always located at different positions on the screen between trials and phases. Offset stimuli (red disks) were always presented at the same location as the onset stimuli of their respective phase. Additionally, participants were explicitly instructed not to use counting strategies to avoid influencing their temporal judgments (Rattat & Droit-Volet, 2012).

Target Durations: We selected a range of durations that included both sub-second and supra-second intervals of 600, 900, 1300, 1900, 2700, and 4000 ms.

Experimental Blocks: Each participant completed 3 blocks using the discrete reproduction method and 3 blocks using the bracket reproduction method. The order of the blocks was counterbalanced across participants. Each block comprised 60 trials, each including 10 repetitions of each target duration in random order. This added up to 60 repetitions per target duration per participant, split evenly between the two reproduction methods.

Measures

Reproduction times were measured differently depending on the reproduction method employed. In all instances, reproduction time began after the presentation of the white disk in the reproduction phase.

Discrete Method Blocks: Reproduction time was determined as the elapsed time until the first moment of pressing the SPACE key during the reproduction phase.

Bracket Method Blocks: Two points were recorded: the start of the bracket (elapsed time until the first SPACE key press during the reproduction phase) and the end of the bracket or stop time (elapsed time until the key release). From these, we calculated the bracket length (time between start and stop) and the reproduction time (midpoint between start and stop), which was considered analogous to the discrete method's measure.

The use of the midpoint of the bracket as the reproduction time is based on Kladopoulos et al. (1998), who proposed it as analogous to the PSE, representing the perceived target duration. Further tests that are described in the results section were performed to validate this selection.

Predictions

Our first aim was to validate the bracket reproduction method against the discrete method by comparing their accuracy and precision across target durations. We also evaluated whether both methods consistently demonstrated robust features of time perception, such as scalar invariance. We hypothesized that reproduction times from the discrete method would closely match the midpoints of the brackets from the bracket method.

Secondly, to further explore the bracket method's potential as a measure of uncertainty, we analysed the relationships between start and stop times, and how bracket length correlated with variability in reproduction estimates and target duration changes. We anticipated a positive correlation between bracket length and variability, with both increasing in line with duration magnitude, due to the scalar property of time.

RESULTS

Data Filtering

Trials were excluded if the reproduction times or bracket lengths (in bracket method blocks) deviated by more than 2 standard deviations from the average for each participant, method, and duration. This aimed to exclude invalid trials where the reproduction value was not related to the perceived duration. These included cases where participants might have mistakenly delayed their response by confusing the learning and reproduction phases, or instances where impulsive reactions or involuntary key releases resulted in unusually short bracket measures or reproduction times.

This resulted in the exclusion of 7.8% of trials from the bracket method blocks and 4.6% from the discrete method blocks.

Task validation

Performance

First, we directly compared time reproduction estimates from the discrete and bracket reproduction methods (using the midpoint of the bracket as the estimate for the latter). This comparison revealed a remarkable similarity between the two methods in terms of error direction, magnitude, and variability. The average estimates from both methods clearly overlapped, suggesting that the bracket reproduction method is a viable alternative to the traditional approach (see Figure 5.6A).

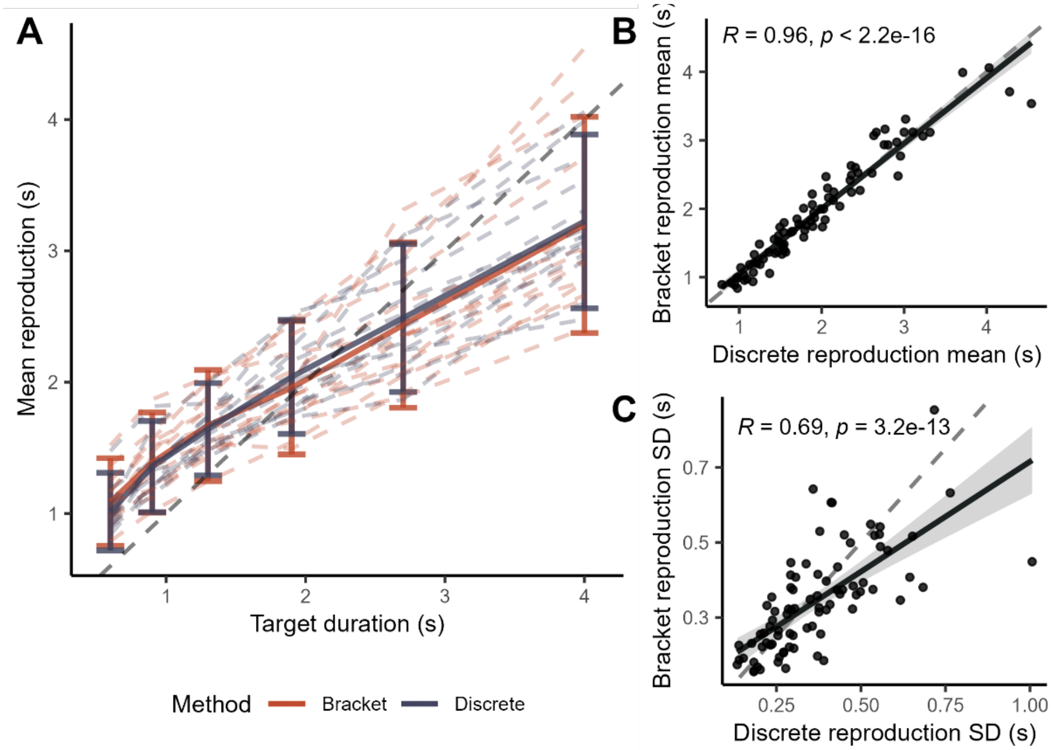


Figure 5.6. Performance comparison between methods. ***(A)*** *Reproduction times as a function of target duration. Bold lines represent the aggregate average between participants. Dashed lines represent individual participants' data. Correlation of reproduction means* ***(B)*** *and standard deviations* ***(C)*** *between methods. Each data point is calculated as the average or standard deviation of reproduction for each participant and target duration.*

A regression analysis using a power function ($y = a \cdot x^b$) demonstrated a strong and significant relationship between target durations and reproduced times for both the discrete (R^2 = 0.74, F(1,2401) = 6706, *p* < 0.001, coefficients a = 0.31, 95% CI = [0.3, 0.32], *p* < 0.001, and b = 0.6, 95% CI = [0.59, 0.62], *p* < 0.001) and bracket (R^2 = 0.65, F(1,2310) = 4306, *p* < 0.001, coefficients a = 0.33, 95% CI = [0.31, 0.34], *p* < 0.001, and b = 0.55, 95% CI = [0.54, 0.57], *p* < 0.001) methods.

The high degree of consistency between reproduction estimates from both methods was further analysed by correlating the parameters of reproduction times across methods. There was a very high correlation between the mean reproduction times of each participant and target duration (r(84) = 0.96, *p* < 0.001), indicating similar accuracy across both methods (see Figure 5.6B). Additionally, a substantial correlation was found for the variability of these reproductions, measured by the standard deviation (r(84) = 0.69, *p* < 0.001),

S3

indicating consistent precision in time estimation across methods (see Figure 5.6C).

To further validate the midpoint of the bracket as the optimal representation of discrete reproduction time, a linear regression analysis was conducted using the average reproduction time from the discrete method to predict the bracket method's average midpoint. This analysis yielded an intercept of 0.05326 (p = 0.406), showing no significant difference between the discrete reproduction time and the midpoint of the bracket, and a slope of 0.97138 ($p < 0.001$), indicating a nearly one-to-one relationship between the two measures. These findings strongly support the midpoint of the bracket as a direct analogue to the discrete method's reproduction time.

Comparison with Time Perception Phenomena

We also examined how well both methods conformed to known phenomena in time perception research, such as Vierordt's law and the scalar property of timing (Weber's law). If both methods are interchangeable, these phenomena should be observable to the same degree in each case.

Vierordt's law is a robust finding in time estimation where short durations tend to be overestimated and long durations tend to be underestimated (J. H. Wearden, 2023). In line with this effect, our data evidenced a strong negative correlation between target duration and average error ($r(84) = -0.83$, $p < 0.001$ for the discrete method; $r(84) = -0.77$, $p < 0.001$ for the bracket method), which confirmed the presence of Vierordt's law in both methods.

The scalar property of timing was also evident in both methods, with an increase in the standard deviation of reproductions as a function of target duration ($r(84) = 0.58$, $p < 0.001$ for the discrete method and $r(84) = 0.47$ $p < 0.001$ for the bracket method). This aligns with scalar timing theory, which posits that the precision of time perception scales with the timed interval itself (Gibbon, 1977; Malapani & Fairhurst, 2002).

Both comparisons are illustrated in Figure 5.7. These results reinforce the behavioural equivalence of the two methods, indicating that both are equally capable of capturing inherent phenomena in temporal estimates.

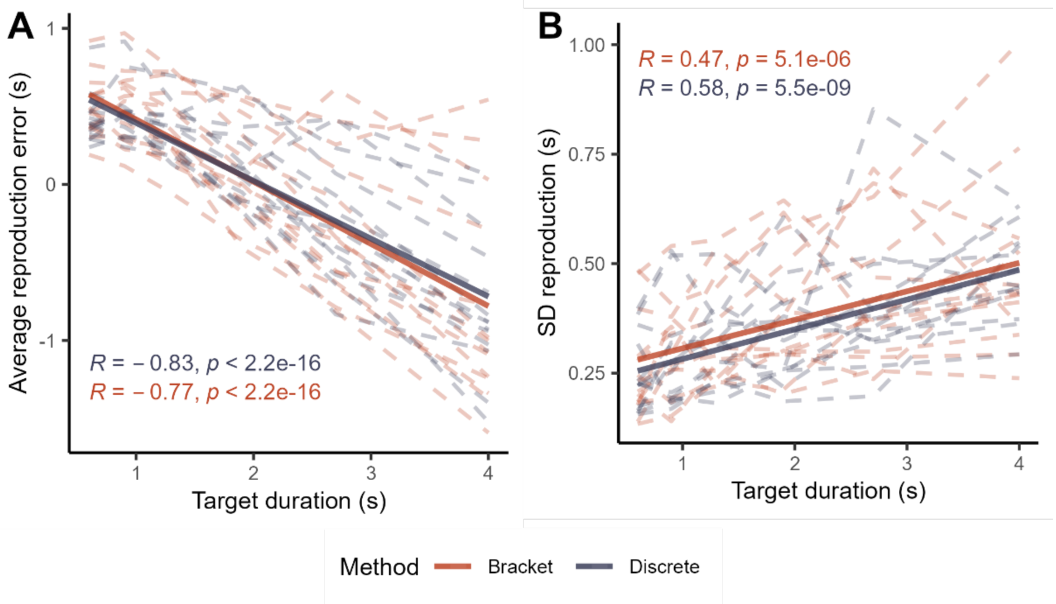


Figure 5.7. Comparison of Weber's law ***(A)*** *and Vierordt's law* ***(B)*** *at each method. Solid lines represent the aggregate data among participants while dashed lines represent individual participants' data.*

Bracket measure of Uncertainty

Once we checked that the bracket method can be equivalent to the traditional reproduction method, we wanted to address the second aim of this study; to assess the potential of this method for measuring uncertainty over the traditional one.

To do so, we examined how the bracket length varied under conditions of expected uncertainty, as well as how it could relate to other measures of uncertainty.

Following the scalar property of timing, we hypothesized that if uncertainty increases with target duration, bracket length should also follow this increase. To test this, we first standardized the bracket lengths by normalizing them within each participant. This was done to remove individual differences or biases towards more conservative or liberal bracket strategies and gave us a measure of how long each participant is producing a given bracket in relation to how long they usually do. Then, we performed a regression analysis where we fitted a power function that revealed a robust and positive relationship between the averaged standardized bracket length and target duration (R^2_{adj} = 0.86, $F(1,82)$ = 518.9, $p < 0.001$, with coefficients a = 0.74, 95% CI = [0.7,0.78], $p < 0.001$, and b = 0.52, 95% CI = [0.47,0.56], $p < 0.001$).

Participants tended to extend their brackets at longer target durations (expectedly those that generated more uncertainty), suggesting that the bracket length effectively captures a key aspect of uncertainty consistent with the scalar nature of time estimation (see Figure 5.8A).

To further validate bracket length as an indicator of uncertainty, we examined its relationship with another common uncertainty index, the variability of time reproductions. Here, we also normalized the bracket length not only for each participant but also for each target duration. This was done to remove the explained variability due to the scalar property already mentioned. We used a Deming regression to account for measurement errors from both variables. The analysis showed a significant relationship with a slope of 6.57 (95% CI: 3.77, 9.36), an intercept of -2.34 (95% CI: -3.32, -1.47) and an error variance ratio of 0.13 (see Figure 5.8B). This indicates a positive relation between bracket length and the standard deviation of time estimates, which suggests that those cases in which participants are more variable (supposedly due to uncertainty) are also those conditions in which they produce longer brackets, probably to compensate for this uncertainty.

Altogether, these results reinforce the bracket length's role as a reliable indicator of uncertainty that can be introduced in reproduction tasks without any harm to participants' performance.

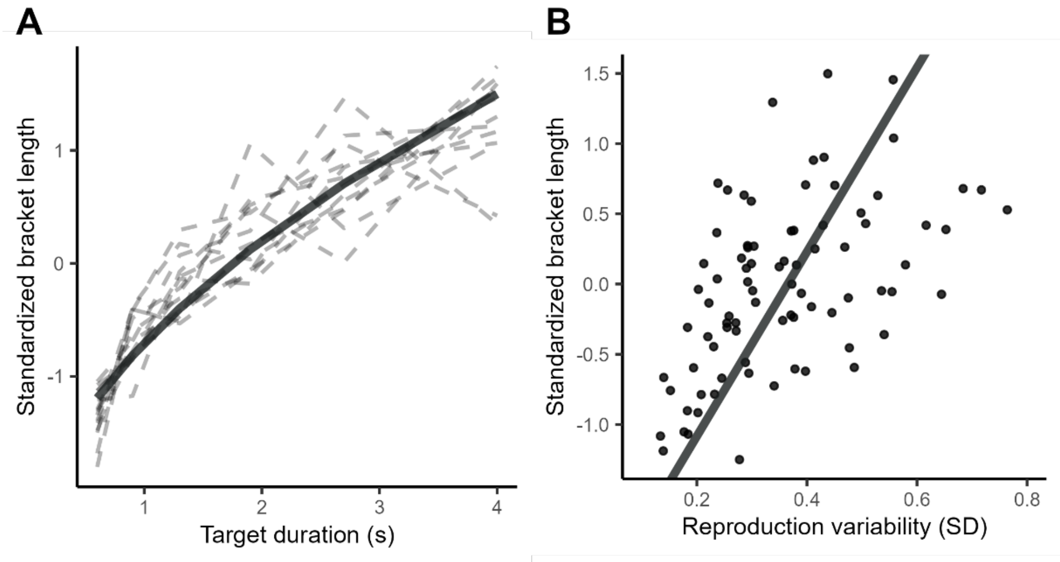


Figure 5.8. ***(A)*** *Relationship between standardized bracket length and target duration. The solid line represents the general trend among participants, while the dashed lines represent individual participants' data.* ***(B)*** *Deming regression of standardized bracket length as a predictor of reproduction variability measured as standard deviation.*

Variance of Start and Stop Times

To analyse how the start and stop times of the bracket varied between them and across the different durations, we fitted a generalized linear mixed model with a Gamma distribution to the ratio of variances of stop by start times (σ^2_{stop}/ σ^2_{start}), including target duration as a fixed effect and participant as random effect. To make the results more interpretable, we included an offset of 1 to test the hypothesis that the variance ratio would differ from 1, which would mean that start and stop times are differentially variable.

Results showed that the intercept was significantly greater than 1 ($\hat{\beta}_0$ = 1.86, SE = 0.27, z = 3.22, p = 0.001), indicating that stop time variance was, on average, and apart from the duration effects, 0.86 times greater than start time variance. The significant negative slope coefficient ($\hat{\beta}_1$ = -0.07, SE = 0.03, z = -2.62, p = 0.009) indicates a convergence of variance ratios towards 1 with increasing target durations, which suggests the presence of some additive noise (see Figure 5.9B).

As explained earlier, if the distance between both thresholds increases (which we interpret as the bracket length), the difference in variability between the start and stop times also increases. This occurs due to the differential accumulation of noise at each threshold. When the first threshold (measured as the start time) is reached sooner, there is less time for random noise to accumulate. Conversely, a delayed stop time allows for more noise accumulation. However, if the increase in the distance between thresholds does not keep pace with the increase in duration, the difference in variability that was significant at shorter durations diminishes at longer durations. This is because the variability due to noise between thresholds becomes negligible compared to the total noise accumulated before reaching the first threshold.

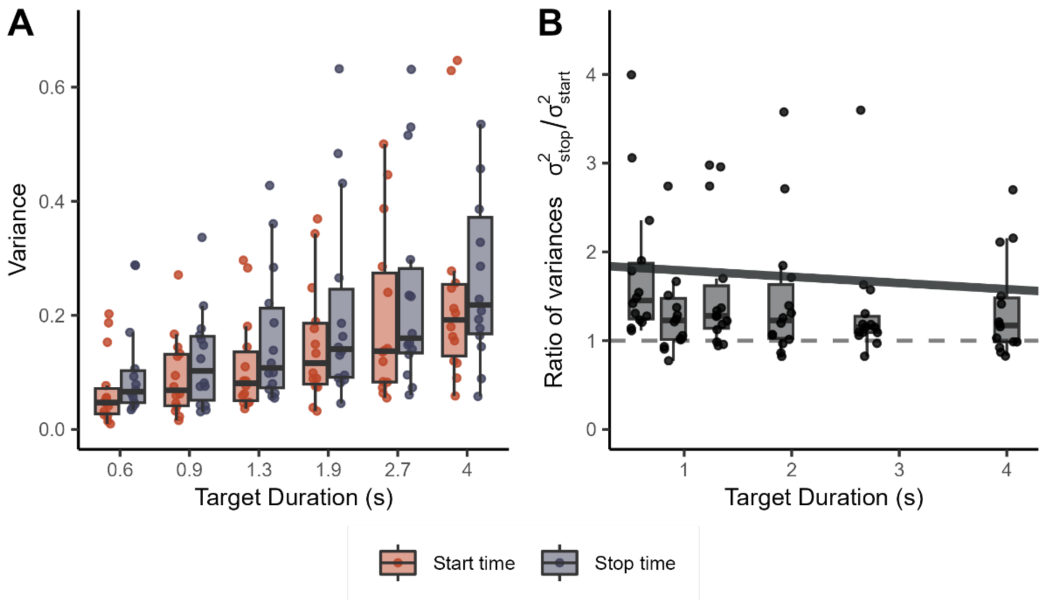


Figure 5.9. ***(A)*** *Variance of start and stop times calculated from each participant and target duration.* ***(B)*** *Ratio of variances at each target duration. Dashed line represents equal variance, solid line represents the predicted variance fit from the model.*

Finally, we used the bracket length measure to further assess the contribution of additive and multiplicative noise components. Using the same structure as Equation (5.1, we fitted a linear model of the reproduced duration as a predictor of the semi-threshold range (half of the bracket length). Following the rationale we just mentioned, the intercept reflects the additive component, the amount that is invariable across target durations, while the slope indicates the multiplicative component, which proportionally increases according to the increase of target duration.

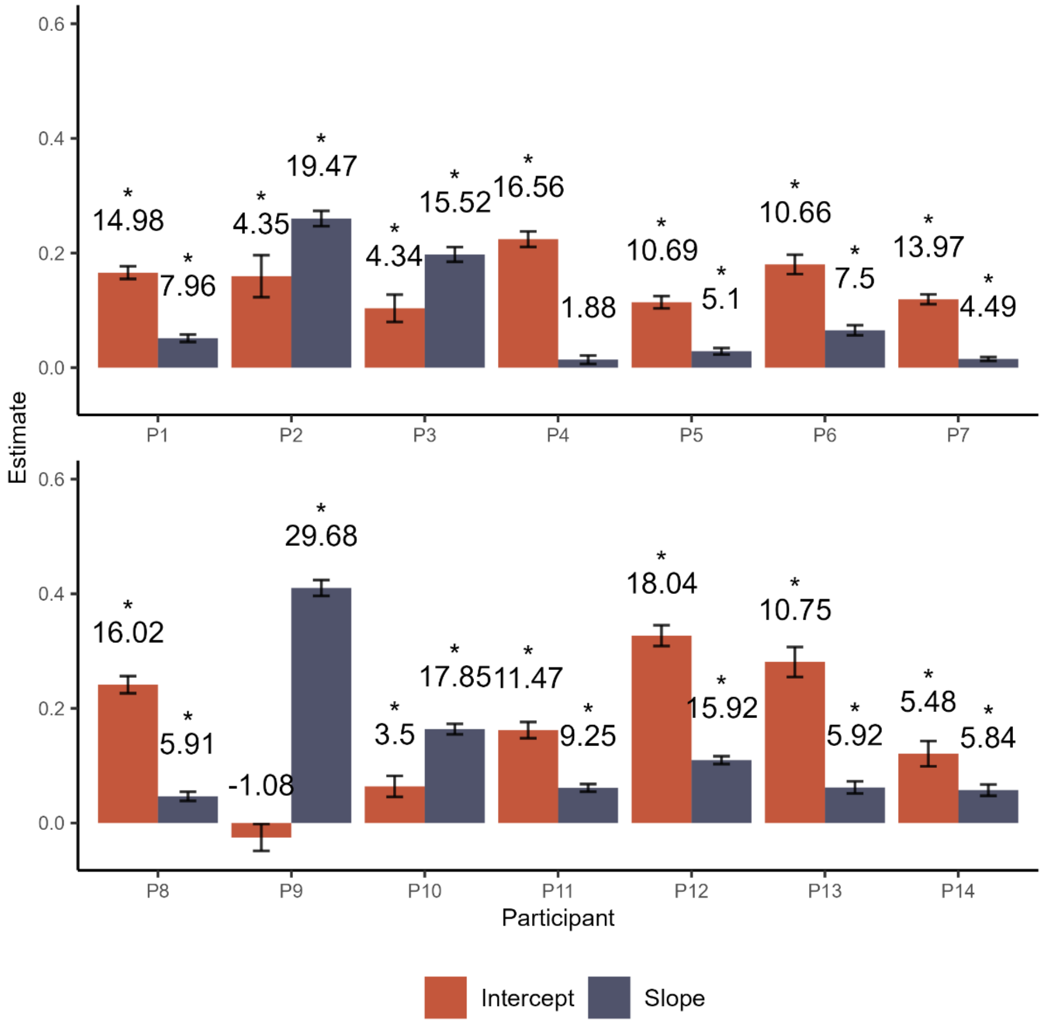


Figure 5.10. Parameters of the bracket components estimated for each participant. Intercepts represent the additive component and slopes represent the multiplicative component. Numbers above the bars represent the t value. Significant coefficients are marked with "".*

For almost all participants, both intercept and slope were significantly different from zero ($p < 0.001$), indicating contributions of both additive and multiplicative components (see Figure 5.10). Some participants had a high baseline bracket with minimal increases for longer durations, while others showed a stronger duration effect on bracket length. See Figure 5.11 for representative examples of participants with predominantly additive, multiplicative, or combined components. With this, the bracket measure proved to be a useful tool for assessing the nature of perceptual decision thresholds in quantitative timing tasks.

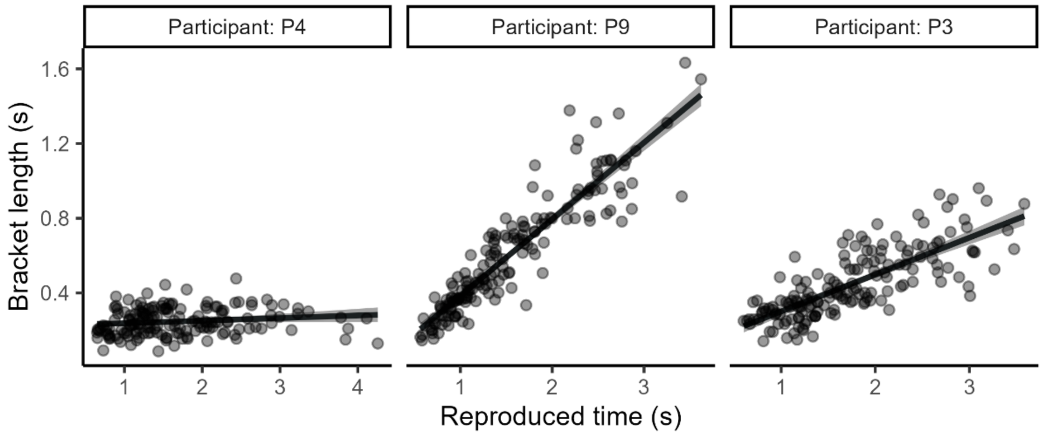


Figure 5.11. Representative examples of participants with low multiplicative but considerable additive bracket components (P4), high multiplicative but null additive bracket components (P9), and a combination of both types of bracket components (P3).

DISCUSSION

Given the relevance of uncertainty in time perception research, our study aimed to provide a methodological tool that overcomes some of the caveats that are usually faced when trying to obtain a measure of uncertainty in duration estimation tasks.

We evaluated the potential of the bracket reproduction method in measuring time perception and compared it with the traditional discrete reproduction method. Our primary goal was to determine whether both methods are equivalent in precision and accuracy and their ability to adhere to common timing phenomena.

Our results confirmed that the discrete and bracket reproduction methods yield equivalent results. Although one might expect that asking for a range instead of a discrete response could alter the participants' reproduction process, our findings indicate remarkably consistent performance across both methods. This consistency was evidenced by the high correlation between reproduction times from discrete responses and the midpoints of the brackets. Additionally, the variability of these estimates remained consistent across methods, highlighting that the apparently added complexity of the response did not reduce precision.

Furthermore, both methods adhered to the traditional conception of the scalar property of timing, where the variability of discrete reproductions and bracket midpoints scaled linearly with the target duration (Gibbon & Church, 1990; Rakitin et al., 1998). The presence of Vierordt's law was also consistent across methods, with shorter durations typically overestimated and longer durations underestimated, indicating a central tendency effect. These parallel outcomes support the interchangeability of both methods and affirm that asking participants to bracket target time does not compromise the assessment of time perception and its associated phenomena.

Our second objective was to explore the bracket interval as a direct measure of uncertainty in time perception. Traditional methods often struggle to capture the subtle nuances of how uncertainty manifests in time estimation, typically inferring it from the variability across multiple reproductions. By adopting the bracket method, we aimed to bypass some of these limitations and provide a more efficient measure.

Our findings suggest that the bracket length obtained in a single trial can represent the variability of multiple discrete reproductions of the same target duration. This approach offers a more efficient alternative to methods like the PI procedure (Rakitin et al., 1998), which require multiple responses within a single trial and often the application of reward dynamics, making them less suitable for certain studies.

Another way to relate bracket length to uncertainty is through the scalar property of timing, which posits that uncertainty increases proportionally with the magnitude of the timed stimuli (Gibbon & Church, 1990; Rakitin et al., 1998). Our results align with this principle, demonstrating that both discrete reproductions and bracket midpoints become more variable as durations increase. Additionally, we found that bracket length increases with target duration, indicating that participants produce longer brackets in conditions with greater expected uncertainty. This highlights that, based on the scalar property of timing, bracket length could serve as a measure of uncertainty in reproduction tasks.

To better understand how the bracket is defined, we explored how computational models of timing would predict these types of responses. Ramping activity or pulse-accumulating models suggest that perceptual decisions are based on the accumulation of subjective time to certain thresholds (Gibbon & Church, 1990; Simen et al., 2016). We proposed the bracket as a proxy for these decision thresholds, with the start of the bracket indicating when the first threshold is reached and the stop indicating when differences are sufficient to be discriminated again. The observed variability between start and stop times showed that stop times were significantly more variable than start times, likely due to the accumulation of noise in the process of reaching the thresholds (Simen et al., 2016). Given that stop times require more accumulation, it is logical to assume more noise in the second threshold. This supports the idea of the start and stop points of the bracket as a proxy of the perceptual decision thresholds.

However, the relative difference between these variabilities decreased as target durations increased (see Figure 5.9), suggesting the presence of some additive noise. If the noise in the accumulating process is somewhat constant, the absolute difference in variability would increase linearly at both start and stop times, but the relative difference would decrease proportional to the duration's magnitude. Our findings of a decrease in the relative difference between variabilities of start and stop times as durations increase indicate the presence of additive noise. This was further reinforced by the bracket model results, showing significant contributions of both additive and multiplicative components in nearly all participants.

Such findings support the hypothesis that both additive and multiplicative noises could be integral to the timing process and indicate possible interactions between these types of noise. This highlights the potential of the bracket method to dissect the contributions of additive and multiplicative noise in timing estimation and help characterize the transducer function for duration in a unique way.

We demonstrated how the bracket method could be linked to other ways of assessing uncertainty with quantitative tasks, but further comparisons could enrich the value of this method and provide more support for methodological advancements. In decisional tasks, which often require comparison or discrimination of time intervals, a psychometric function typically provides a measure of sensitivity from its slope (Wichmann & Hill, 2001). Since sensitivity is directly related to uncertainty, linking it with the bracket length could offer an advantageous alternative in scenarios that require sensitivity measures but would benefit from a quantitative approach.

Other approaches to measuring uncertainty in time perception involve confidence judgments, which are often used in psychophysics tasks to assess the metacognitive level of task performance, providing a direct view into participants' perceived reliability of their estimations. For instance, Lamotte et al. (2017) found that confidence judgments correlate with the accuracy of duration estimates in a temporal generalization task. Akdoğan & Balcı (2017) also showed that individuals could introspectively assess their timing errors, linking this awareness to confidence levels. Cropper et al. (2024) and Corcoran et al. (2018) even explored second-order confidence judgments in modified temporal-bisection tasks, asking participants to retrospectively compare pairs of time estimations that they produced themselves during the task. Also, Jovanovic et al. (2023) provided further evidence of the relation between timing accuracy and confidence by revealing that dopamine depletion affects both factors similarly, highlighting the shared neurochemical underpinnings of these processes. While our study does not directly discuss the relationship between confidence and uncertainty, the emerging interest in metacognitive assessments suggested by these studies provides a valuable direction for future research. Specifically, exploring how the bracket method's measure of uncertainty correlates with participants' confidence judgments could offer deeper insights into uncertainty in time perception at different cognitive stages and reveal how much uncertainty we are actually aware of.

Considering the bracket method alongside confidence judgments and discriminability from psychometric functions presents an interesting avenue to further develop the methodological toolkit in time perception. This multifaceted methodology could shed light on the complex dynamics between objective uncertainty, decisional processes, and metacognitive judgments, enriching our understanding of how individuals perceive, estimate, and reflect on their own experience of time.

CONCLUSION

This study has shown that the bracket reproduction method is a highly effective alternative to the traditional discrete reproduction method for measuring time perception. Both methods produced comparable results in terms of accuracy and precision for intervals ranging from 0.6 to 4 seconds. Additionally, our research indicates that the length of the bracket can be a strong indicator of uncertainty. By examining the components of the bracket, we can uniquely address the debate on the roles of additive and multiplicative noise in perceptual estimations. Consequently, the bracket method represents a significant enhancement to the tools available for time perception research, enabling a deeper understanding of the inherent variability in human time perception and shedding light on the cognitive mechanisms involved in timing behaviour.

Part VI

DISCUSSION AND CONCLUSIONS

GENERAL DISCUSSION

Throughout the present thesis, we introduced the field of time perception research, examining the evolution of key models that shaped our understanding of human timing. Then, our primary focus has been on two fundamental aspects: multiple timing, specifically multiple timing, and uncertainty in time perception. The overarching aim was to address the existing gaps in research related to simultaneous multiple timing and to contribute novel approaches to the measurement of uncertainty in time perception.

To achieve these objectives, we conducted three studies. The first two studies centred on exploring multiple timing, while the third study introduced a new method for measuring uncertainty in time perception. In this general discussion, we will summarize how each study addressed the specific objectives of the thesis, discuss the limitations encountered, and propose potential contributions and future directions inspired by our findings.

SIMULTANEOUS MULTIPLE TIMING

Given the limited literature on the effects of simultaneous multiple timing and the inherent complexity of these paradigms, we began our investigation with a relatively simple comparison task. This approach allowed us to observe the potential interference of simultaneous events in our timing processes, even when these events were irrelevant to the task at hand. To further explore the intersection between size and time perception, as suggested by the ATOM theory (Bueti & Walsh, 2009; Choy & Cheung, 2017; Fabbri et al., 2012; Walsh, 2003), we adapted a well-known size illusion paradigm, manipulating duration instead of size.

In line with Objective 1, we examined whether and how the duration of simultaneous distractors affected participants' judgments of the attended target durations. Importantly, in our paradigm, the distractors were irrelevant, as participants were instructed to base their judgments solely on the comparison of the target durations and ignore the surrounding stimuli. Since the target durations being compared were always identical, any observed effects could be attributed to involuntary interference, where irrelevant overlapping events were inadvertently filtered into the perceptual process.

Our findings revealed that interference indeed occurs, with participants' judgments of target durations significantly skewed by the duration of surrounding distractors. Specifically, we observed a central tendency or averaging effect, where the perceived duration of the targets shifted towards a value more similar to that of the distractors. These results are consistent with previous studies that have examined the impact of irrelevant simultaneous events on time estimation. For instance, Kawahara and Yotsumoto (2020) reported a similar pattern, where target intervals were overestimated when accompanied by longer distractors and underestimated when accompanied by shorter distractors. Our comparison paradigm, which aligns with their reproduction task, suggests that the observed effects likely reflect a perceptual bias that generalizes across different timing paradigms rather than being limited to decisional processes.

Moreover, our results also align with those of De Corte and Matell (2016), who also found evidence of an automatic averaging effect in situations involving irrelevant stimuli. This supports the notion that central tendency effects may arise without intentional integration of distractor durations, yet still interfere with the perceptual process.

However, the co-occurrence of opposing effects (central tendency in most participants and repulsion in a few) raises questions about the underlying mechanisms. While adaptation studies based on the duration-channel theory attribute repulsion effects to channel saturation (Heron et al., 2012), this explanation seems unlikely in our case, where the effect was observed after a single presentation rather than through repeated exposure. This suggests that an unknown mechanism may be promoting these effects in our paradigm, suggesting a path for further research to explore the factors that determine the direction of effects in simultaneous multiple timing.

To enhance our understanding of these interferences, and address Objective 3, we developed a computational model grounded in the duration-channel theory. This model is particularly valuable as it predicts the extent to which duration estimates deviate based on the temporal properties of distractors. Unlike more rigid models, our adapted version can account for both the common averaging effect and the rarer repulsion effect, providing a more nuanced understanding of the interference. We also highlight the estimation of the leaking factor, a key component that describes how the effect of simultaneous stimuli is modulated by their similarity to the target. This shows that interference in simultaneous multiple timing is not indiscriminate but rather depends on the degree of similarity between stimuli.

Finally, our attempt to translate a size illusion paradigm to the temporal domain yielded intriguing results. The ATOM theory posits shared mechanisms across modalities, suggesting that the mental representations of size, numerosity, or time are processed in a modality-agnostic manner (Bueti & Walsh, 2009; Choy & Cheung, 2017; Fabbri et al., 2012; Walsh, 2003). In the size illusion we adapted, the effect is robustly contrastive, with perceived size shifting away from distractor sizes (B. Roberts et al., 2005). We then expected to find the same type of effect in the temporal domain. Although to our knowledge there is no previous direct translation of this size illusion to the temporal domain, previous research using this same size illusion effect has shown that altering the perceived size of visual stimuli can directly affect the perceived duration (Bratzke et al., 2023; Ono & Kawahara, 2007). However, we must relate these studies carefully, as while this interaction suggests a link in terms of magnitude between size and duration, it does not necessarily indicate that the entire perceptual process uses the same mechanisms. It could simply show that the strength of the size illusion or the effect of size on perceived duration is sufficient to prevail when adding this extra step.

Answering Objective 2, our results do not support the idea that the perceptual mechanisms are fully shared between the two modalities. Although we made a direct translation of the paradigm of the illusion from size to time, the effects we found were the opposite. If the mechanisms were the same, we would have observed that perceived target durations always shifted away from distractor durations. Instead, we found that in most cases, target durations were averaged towards distractor durations.

Additionally, in the case of duration, the effects seem to fade as distractors and targets become more different, whereas the size-contrast effect actually benefits from an evident difference between stimuli (B. Roberts et al., 2005). With this, we conclude that time estimation, although affected in many cases by other modalities such as size, is determined by its own biases and mechanisms.

OPTIMAL SAMPLING OF MULTIPLE EVENTS

Building upon the insights gained from the first study, the second study aimed to explore the concept of simultaneous multiple timing from a different perspective, one that considers it not merely as an interference but as a crucial ability in complex, real-world tasks (Brown & West, 1990; Buhusi & Meck, 2005). In the first study, we observed that the leaking factor, representing the permeability of external durations into the time estimation process, was associated with better discrimination when intervals were composed of multiple elements. This finding hinted that integrating durations from simultaneous events might not necessarily constitute interference but could be beneficial or even necessary in certain contexts.

Thus, to further explore this idea and in contrast to the more classic design of the previous experiment, the task presented in the second study was designed to mirror more complex real-life situations where success depends on the ability to calculate, maintain, and work with multiple intervals at once. This progression aimed to explore the multifaceted nature of simultaneous multiple timing, providing a more comprehensive understanding of the implications and limitations of tracking multiple simultaneous durations.

To achieve this, following Objective 4, we designed a novel and more naturalistic task that required participants to monitor unpredictable events in a simulated driving environment. In the task, participants were required to distribute the sampling time to different locations according to the corresponding duration of each of them and the limitations of their own monitoring movements. In order to succeed in the task and maximize the number of detections, they should track the current sampling time, keep in their working memory the duration of each event and compute the time lost due to movement restrictions to guide their behaviour.

One of the key contributions of this study was the development and implementation of an optimal observer model, which provided a framework for predicting participants' detection performance based on their monitoring patterns. This model proved effective in estimating the likelihood of event detection, achieving Objective 6 and offering a useful tool for assessing behaviour in complex temporal tasks. However, while the model accurately predicted detection rates, it also revealed that participants, although selecting an appropriate monitoring strategy, did not always optimally adjust their monitoring patterns in response to changes in the temporal structure of the environment.

In relation to Objective 5, the suboptimal adjustment observed suggests that additional factors may influence participants' monitoring strategies, which were not fully captured by the current model. This raises important questions about the underlying mechanisms guiding these strategies. For instance, while the model predicts detection based on a rational allocation of monitoring resources, real-world decision-making often involves heuristics, cognitive biases, and other factors that may lead to deviations from the optimal strategy (Balcı & Simen, 2016; Ratcliff, 1978). Future research could explore these additional components, potentially integrating them into the model to enhance its predictive power and provide a more comprehensive understanding of the factors influencing temporal monitoring in dynamic environments.

In summary, the second study extends our understanding of simultaneous multiple timing by framing it as an essential skill in complex, real-world tasks. The development of the optimal observer model offers a promising tool for predicting behaviour in such tasks, though further research is needed to refine it and explore additional factors that influence temporal monitoring strategies. The study also strengthens the connection between the concepts explored in the first study, highlighting the dual role of simultaneous multiple timing as both an interference and a critical ability, depending on the context (de Montalembert & Mamassian, 2012; Morgan et al., 2008).

NEW METHOD FOR MEASURING UNCERTAINTY

In addition to exploring the complexities of simultaneous multiple timing, the third study in this thesis focused on advancing our understanding of uncertainty in time perception. As seen through the different studies and even in the presentation of time perception models, uncertainty plays a critical role in temporal judgments, influencing the variability and reliability of time estimates. Despite its importance, the measurement of uncertainty in time perception has traditionally relied on methods that are either indirect or limited in scope, such as variability in estimates or the slope of the psychometric function. Our aim in this study was to introduce a more direct and informative method for measuring uncertainty in quantitative timing tasks.

The key innovation of this study was the use of the bracket method, a modified reproduction task (Kladopoulos et al., 1998), as a tool to capture uncertainty on a trial-by-trial basis. Unlike traditional methods, which either provide a global measure of uncertainty across an entire task or depend on explicit metacognitive judgments, the bracket method allows for the measurement of uncertainty associated with each individual response. In summary, participants were asked not only to reproduce a time interval but also to indicate a range of possible values within which they believed the true interval might fall. This approach offers a richer dataset, providing insight into both the shifts in time estimates and the confidence participants have in those estimates.

One of the central findings of this study, defined by Objective 7, was that the bracket method produced results closely aligned with those obtained using the traditional reproduction method, ensuring that the new approach did not compromise the accuracy or validity of time estimates. This compatibility is crucial because it demonstrates that the bracket method can be adopted without losing the benefits of pre-established approaches while offering the additional advantage of measuring uncertainty directly.

Beyond demonstrating the validity of the bracket method, the study also explored its potential to uncover the nature of noise in timing tasks. The results indicated that the length of the bracket, defined as the range of values that participants bracketed their estimate into, correlated positively with the variability of the reproduced intervals. This relationship suggests that as participants' uncertainty in their timing estimates increased (reflected by a wider bracket), the variability in these estimates also increased. Moreover, the bracket length was observed to increase with the magnitude of the duration being estimated, which aligns with the scalar property of timing, where uncertainty tends to increase proportionally with the duration of the interval. These findings provide strong evidence that bracket length serves as a valid measure of uncertainty in time reproduction, which fulfils Objective 8 and highlights the bracket method as a powerful tool for future research in time perception. With this, being able to directly measure uncertainty on a trial-by-trial basis opens up new possibilities for studying how uncertainty interacts with various cognitive processes, how it is modulated by different task conditions, and how individual differences in temporal processing might be better understood.

Beyond providing a direct measure of uncertainty, the bracket method also offers unique insights into the nature of noise in timing tasks. Motivated by Objective 9, the additional metrics derived from the bracket responses allowed us to investigate how uncertainty and noise, vary across different duration magnitudes. This is particularly relevant for examining the manifestation of the scalar property of timing, considered a form of Weber's law in time perception (Gibbon, 1971, 1977; Gibbon et al., 1984; Gibbon & Church, 1990). Although it posits that noise in the perceptual process should be proportional to the magnitude of the stimulation (Buhusi & Meck, 2005; Gibbon, 1977; Grondin, 2010; Matell & Meck, 2000), in some cases, this property does not behave uniformly, raising questions about the underlying nature of noise. For example, in our first study, we discussed whether the nature of noise in timing tasks could be additive instead of multiplicative, as is commonly assumed.

Distinguishing between these types of noise is crucial because fitting such findings with Weber's law can be challenging and often requires specific combinations of transducer mechanisms and noise types to maintain compliance with the rule (Zhou et al., 2024). The bracket method, by providing additional metrics on a trial-by-trial basis, facilitates this discussion by enabling us to observe how uncertainty evolves through the magnitude range more precisely at the same time as we derive a transducer, and even allows us to fit models that can separately assess the contributions of additive and multiplicative noise components within each individual participant.

Using this method, we found mixed contributions of additive and multiplicative noise across participants. Some exhibited high levels of additive noise but low levels of multiplicative noise, while others showed the opposite pattern or even a more balanced combination of both. This variability is particularly interesting as it highlights individual differences in how noise manifests in timing tasks. By opening new avenues to discriminate which type of noise is predominant in a participant, the bracket method provides valuable tools for studies focused on factors that might selectively influence additive or multiplicative noise differently.

In summary, the third study makes a substantial contribution to the field of time perception by introducing and validating the bracket method as a powerful tool for measuring uncertainty. The method not only aligns with traditional approaches but also offers new possibilities for investigating the nature of noise and how it varies across the duration magnitude range. By providing a trial-by-trial measure of uncertainty, the bracket method opens up new possibilities for research, particularly in contexts where understanding the variability of temporal judgments is essential. Additionally, by distinguishing differential contributions of additive and multiplicative noise, the bracket method enhances our understanding of individual differences in timing processes and provides a valuable resource for future research exploring the underlying mechanisms of temporal perception.

LIMITATIONS

While the studies presented in this thesis significantly advance our understanding of time perception, particularly in the context of simultaneous multiple timing and uncertainty, several limitations must be acknowledged. First, the relationship between size and time perception, often described as interrelated, remains unclear in our findings from Study 1. Although we anticipated similar effects as in the size illusion, our results diverged, suggesting that these perceptual domains may operate differently in certain contexts. Also, the duration-channels model, while robust in detecting and measuring both central tendency and repulsion effects, does not fully explain why each of these opposing effects occurs within the same paradigm. The model effectively fits the observed data, but we lack a clear understanding of the underlying mechanisms that determine when and why these different effects arise. Moreover, this model may oversimplify the interaction between distractor and target durations, particularly in real-world scenarios with more complex and diverse temporal structures. As such, the generalizability of these findings in more naturalistic settings remains uncertain.

This approximation was addressed in Study 2, but although our model successfully predicts participants' probability of detecting temporal events, it does not fully account for the suboptimal adjustment observed in their monitoring strategies. This suggests that additional factors, possibly including cognitive biases, heuristics, or other real-world decision-making influences, may not have been captured by the current model. Incorporating these factors might be necessary to improve how the model explains the cognitive process involved in timing in complex and dynamic environments.

Finally, regarding the new approach to measuring uncertainty that we proposed, while the new task introduced proved to be a valid proxy for traditional measures of uncertainty, its effectiveness was only tested within the specific context of a very simple quantitative timing task. Therefore, we cannot guarantee that this measure would hold up in more complex or varied timing tasks. Moreover, the selection of a specific reference point within the bracket as the reproduction estimate presented a challenge. Although we opted for the central point, as suggested by previous literature, the justification for this choice remains somewhat arbitrary. Nonetheless, our results indicate that this selection closely aligns with traditional reproduction times, suggesting it may be the most accurate representation.

FUTURE DIRECTIONS

The findings of this thesis open several avenues for future research. The development of practical applications based on these findings could have significant implications, particularly in fields where precise timing is critical, such as sports, education, and clinical interventions. Future research should explore how the methodologies and models developed in this thesis could be adapted for use in these applied settings, potentially leading to new tools and strategies for enhancing temporal cognition.

Each of the computational models proposed in this thesis has contributed to explaining the phenomena observed within our specific paradigms. However, these models should also be tested beyond these controlled environments to assess their generalizability. Enhancing these models to incorporate additional factors, such as cognitive biases or environmental variability, could provide a more comprehensive understanding of time perception across different contexts. Expanding the predictive power of these models will be crucial for their application in more complex, real-world scenarios.

Additionally, given the complexity of time perception, it is essential to recognize that real-life situations requiring the tracking of durations may differ significantly from the tasks used in laboratory settings. To address this, future research should aim to simulate more ecologically valid environments, potentially through the use of virtual reality or augmented reality technologies. These tools could create dynamic and complex scenarios that better mimic the temporal demands individuals face in everyday life, allowing researchers to test the robustness of their models and findings under more realistic conditions. Approaches that try to approximate the real-life demands of timing are vital for strengthening the generalizability of our conclusions.

Considering the critical role of uncertainty in time estimation, the new method proposed in this thesis should be extensively tested across different magnitudes, manipulations, and levels of complexity. Further validation will be crucial to establish its reliability and applicability in various contexts. This method also holds potential for integration into future studies where uncertainty is a significant factor, offering a more precise approach to understanding and quantifying temporal uncertainty. By broadening its application, researchers could gain deeper insights into how uncertainty shapes cognitive processes in time perception and related domains.

CONCLUSIONS

The present thesis proposed significant contributions to the field of time perception, particularly in the underrepresented area of simultaneous multiple timing. While time perception has been extensively studied, the specific challenges and complexities associated with simultaneously processing multiple temporal events have been scarcely explored. This gap in the literature makes the findings presented here particularly valuable, as they offer new insights into how our cognitive systems handle the intricate demands of multiple timing in various contexts.

A key aspect that illustrates how the thesis approaches this field is the conception of the dual role of simultaneous multiple timing, both as a potential source of interference and as a critical ability required for success in complex, real-world tasks. The first two studies highlighted this duality by demonstrating that while simultaneous timing can introduce interference, it can also be harnessed as an essential skill in more naturalistic and dynamic environments.

This exploration of multiple timing is complemented by the integration of computational modelling, which has been used throughout the thesis to deepen our understanding of the processes underlying time perception. These models, such as the duration-channel leaking model and the optimal observer model, not only help explain the behavioural data but also allow us to predict how various factors, like the leaking factor or monitoring strategies, influence temporal judgments. By coupling behavioural findings with modelling approximations, this thesis contributes to both the theoretical framework and practical understanding of time perception.

In addition to these behavioural and theoretical contributions, the thesis introduces methodological advancements that provide new tools for future research. The bracket method, developed in the third study, offers a novel approach to measuring uncertainty in time perception, providing a direct, trial-by-trial measure that has not been possible with traditional methods. This method not only aligns with existing approaches but also enhances our ability to study the nature of noise in timing tasks, offering detailed insights into how uncertainty evolves across different duration magnitudes. This also opens up new possibilities for exploring individual differences in time perception. By distinguishing between additive and multiplicative noise components, the method allows for a more nuanced understanding of how different types of noise contribute to timing variability, potentially informing future research on factors that might selectively influence these components.

As we look to the future, the potential for further investigation into simultaneous multiple timing is vast. We hope that the methodological tools proposed here as well as the ideas presented through the diverse computational models will lay the ground for future research that will continue to explore and expand the theoretical and practical boundaries of how we perceive and process time.

C

REFERENCES

REFERENCES

Acerbi, L., Wolpert, D. M., & Vijayakumar, S. (2012). Internal Representations of Temporal Statistics and Feedback Calibrate Motor-Sensory Interval Timing. *PLoS Computational Biology*, *8*(11), e1002771. https://doi.org/10.1371/journal.pcbi.1002771

Addyman, C., French, R. M., & Thomas, E. (2016). Computational models of interval timing. *Current Opinion in Behavioral Sciences*, *8*, 140-146. https://doi.org/10.1016/j.cobeha.2016.01.004

Akdoğan, B., & Balcı, F. (2017). Are you early or late?: Temporal error monitoring. *Journal of Experimental Psychology: General*, *146*(3), 347-361. https://doi.org/10.1037/xge0000265

Ayhan, I., Revina, Y., Bruno, A., & Johnston, A. (2012). Duration Judgments Over Multiple Elements. *Frontiers in Psychology*, *3*(NOV), 1-8. https://doi.org/10.3389/fpsyg.2012.00459

Balcı, F., & Simen, P. (2016). A decision model of timing. *Current Opinion in Behavioral Sciences*, *8*, 94-101. https://doi.org/10.1016/j.cobeha.2016.02.002

Balcı, F., Wiener, M., Çavdaroğlu, B., & Branch Coslett, H. (2013). Epistasis effects of dopamine genes on interval timing and reward magnitude in humans. *Neuropsychologia*, *51*(2), 293-308. https://doi.org/10.1016/j.neuropsychologia.2012.08.002

Beck, M. R., Hong, S. L., Van Lamsweerde, A. E., & Ericson, J. M. (2014). The Effects of Incidentally Learned Temporal and Spatial Predictability on Response

Times and Visual Fixations during Target Detection and Discrimination. *PLoS ONE*, *9*(4), e94539. https://doi.org/10.1371/journal.pone.0094539

Bisson, N., & Grondin, S. (2013). Time Estimates of Internet Surfing and Video Gaming. *Timing & Time Perception*, *1*(1), 39-64. https://doi.org/10.1163/22134468-00002002

Blakemore, C., Carpenter, R. H. S., & Georgeson, M. A. (1970). Lateral Inhibition between Orientation Detectors in the Human Visual System. *Nature*, *228*(5266), 37-39. https://doi.org/10.1038/228037a0

Boned, J., & López-Moliner, J. (2022). Duration judgments are mediated by the similarity with the temporal context. *Scientific Reports*, *12*(1), 22575. https://doi.org/10.1038/s41598-022-27168-w

Boned, J., & López-Moliner, J. (2024). Quantifying uncertainty in time perception: A modified reproduction method. *i-Perception*, *15*(0), 1-18. https://doi.org/10.1177/20416695241279675

Bratzke, D., Peris, L., & Ulrich, R. (2023). Time and visual-spatial illusions: Evidence for cross-dimensional interference between duration and illusory size. *Attention, Perception, & Psychophysics*, *86*(2), 567-578. https://doi.org/10.3758/s13414-023-02737-x

Brown, S. W., & West, A. N. (1990). Multiple timing and the allocation of attention. *Acta Psychologica*, *75*(2), 103-121. https://doi.org/10.1016/0001-6918(90)90081-P

Bruno, A., & Cicchini, G. M. (2016). Multiple channels of visual time perception. *Current Opinion in Behavioral Sciences*, *8*, 131-139. https://doi.org/10.1016/j.cobeha.2016.02.028

Bryce, D., & Bratzke, D. (2016). Multiple timing of nested intervals: Further evidence for a weighted sum of segments account. *Psychonomic Bulletin & Review*, *23*(1), 317-323. https://doi.org/10.3758/s13423-015-0877-5

Bueti, D., & Walsh, V. (2009). The parietal cortex and the representation of time, space, number and other magnitudes. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1525), 1831-1840. https://doi.org/10.1098/rstb.2009.0028

Buhusi, C. V., & Meck, W. H. (2005). What makes us tick? Functional and neural mechanisms of interval timing. *Nature Reviews Neuroscience*, *6*(10), 755-765. https://doi.org/10.1038/nrn1764

Burgess, C., Schuck, N. W., & Burgess, N. (2011). Temporal Neuronal Oscillations can Produce Spatial Phase Codes. En *Space, Time and Number in the Brain* (pp. 59-69). Elsevier. https://doi.org/10.1016/B978-0-12-385948-8.00005-0

Burr, D., Rocca, E. D., & Morrone, M. C. (2013). Contextual effects in interval-duration judgements in vision, audition and touch. *Experimental Brain Research*, *230*(1), 87-98. https://doi.org/10.1007/s00221-013-3632-z

Catania, A. (1970). Reinforcement schedules and psychophysical judgment: A study of some temporal properties of behavior. *Wireless Networks - WINET*.

Choy, E. E. H., & Cheung, H. (2017). Linguistic asymmetry, egocentric anchoring, and sensory modality as factors for the observed association between time and space perception. *Cognitive Processing*, *18*(4), 479-490. https://doi.org/10.1007/s10339-017-0817-6

Clarke, A. D. F., & Hunt, A. R. (2016). Failure of Intuition When Choosing Whether to Invest in a Single Goal or Split Resources Between Two Goals. *Psychological Science*, *27*(1), 64-74. https://doi.org/10.1177/0956797615611933

Cona, G., Wiener, M., & Scarpazza, C. (2021). From ATOM to GradiATOM: Cortical gradients support time and space processing as revealed by a meta-analysis of neuroimaging studies. *NeuroImage*, *224*, 117407. https://doi.org/10.1016/j.neuroimage.2020.117407

Corcoran, A. W., Groot, C., Bruno, A., Johnston, A., & Cropper, S. J. (2018). Individual differences in first- and second-order temporal judgment. *PLOS ONE*, *13*(2), e0191422. https://doi.org/10.1371/journal.pone.0191422

Creelman, C. D. (1962). Human Discrimination of Auditory Duration. *The Journal of the Acoustical Society of America*, *34*(5), 582-593. https://doi.org/10.1121/1.1918172

Cropper, S. J., Little, D. R., Xu, L., Bruno, A. M., & Johnston, A. (2024). Measuring the perception and metacognition of time. *Journal of Vision*, *24*(3), 5. https://doi.org/10.1167/jov.24.3.5

De Corte, B. J., & Matell, M. S. (2016). Interval timing, temporal averaging, and cue integration. *Current Opinion in Behavioral Sciences*, *8*, 60-66. https://doi.org/10.1016/j.cobeha.2016.02.004

de Montalembert, M., & Mamassian, P. (2012). Processing temporal events simultaneously in healthy human adults and in hemi-neglect patients. *Neuropsychologia*, *50*(5), 791-799. https://doi.org/10.1016/j.neuropsychologia.2012.01.013

Ebbinghaus, Hermann. (1902). *Grundzüge der psychologie: Vol. I and II*. Verlag von Viet & Co.

Echeverria-Altuna, I., Nobre, A. C., & Boettcher, S. E. P. (2024). Goal-Dependent Use of Temporal Regularities to Orient Attention under Spatial and Action Uncertainty. *Journal of Cognition*, *7*(1), 37. https://doi.org/10.5334/joc.360

Efron, B., & Tibshirani, R. J. (1993). An Introduction to the Bootstrap. En *An Introduction to the Bootstrap*. Chapman and Hall. https://doi.org/10.1201/9780429246593

Fabbri, M., Cancellieri, J., & Natale, V. (2012). The A Theory Of Magnitude (ATOM) model in temporal perception and reproduction tasks. *Acta Psychologica*, *139*(1), 111-123. https://doi.org/10.1016/j.actpsy.2011.09.006

Forstmann, B. U., Ratcliff, R., & Wagenmakers, E.-J. (2016). Sequential Sampling Models in Cognitive Neuroscience: Advantages, Applications, and Extensions. *Annual Review of Psychology*, *67*(1), 641-666. https://doi.org/10.1146/annurev-psych-122414-033645

Gibbon, J. (1971). Scalar timing and semi-markov chains in free-operant avoidance. *Journal of Mathematical Psychology*, *8*(1), 109-138. https://doi.org/10.1016/0022-2496(71)90025-3

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. (1990). Representation of time. *Cognition*, *37*(1-2), 23-54. https://doi.org/10.1016/0010-0277(90)90017-E

Gibbon, J., Church, R. M., & Meck, W. H. (1984). Scalar Timing in Memory. *Annals of the New York Academy of Sciences*, *423*(1), 52-77. https://doi.org/10.1111/j.1749-6632.1984.tb23417.x

Graf, E. W., Warren, P. A., & Maloney, L. T. (2005). Explicit estimation of visual uncertainty in human motion processing. *Vision Research*, *45*(24), 3050-3059. https://doi.org/10.1016/j.visres.2005.08.007

Gregory, R. L. (1980). Perceptions as Hypotheses. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *290*(1038), 181-197. JSTOR.

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

Grondin, S., & Plourde, M. (2007). Judging Multi-Minute Intervals Retrospectively. *Quarterly Journal of Experimental Psychology*, *60*(9), 1303-1312. https://doi.org/10.1080/17470210600988976

Hallez, Q., Damsma, A., Rhodes, D., van Rijn, H., & Droit-Volet, S. (2019). The dynamic effect of context on interval timing in children and adults. *Acta Psychologica*, *192*(May 2018), 87-93. https://doi.org/10.1016/j.actpsy.2018.10.004

Hass, J., & Herrmann, J. M. (2012). The Neural Representation of Time: An Information-Theoretic Perspective. *Neural Computation*, *24*(6), 1519-1552. https://doi.org/10.1162/NECO_a_00280

Heron, J., Aaen-Stockdale, C., Hotchkiss, J., Roach, N. W., McGraw, P. V., & Whitaker, D. (2012). Duration channels mediate human time perception. *Proceedings of the Royal Society B: Biological Sciences*, *279*(1729), 690-698. https://doi.org/10.1098/rspb.2011.1131

Honig, M., Ma, W. J., & Fougnie, D. (2020). Humans incorporate trial-to-trial working memory uncertainty into rewarded decisions. *Proceedings of the National Academy of Sciences*, *117*(15), 8391-8397. https://doi.org/10.1073/pnas.1918143117

Hoppe, D., & Rothkopf, C. A. (2016). Learning rational temporal eye movement strategies. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(29), 8332-8337. https://doi.org/10.1073/pnas.1601305113

Hyafil, A., de la Rocha, J., Pericas, C., Katz, L. N., Huk, A. C., & Pillow, J. W. (2023). Temporal integration is a robust feature of perceptual decisions. *eLife*, *12*, e84045. https://doi.org/10.7554/eLife.84045

Jazayeri, M., & Shadlen, M. N. (2010). Temporal context calibrates interval timing. *Nature Neuroscience*, *13*(8), 1020-1026. https://doi.org/10.1038/nn.2590

Jovanovic, L., Chassignolle, M., Schmidt-Mutter, C., Behr, G., Coull, J. T., & Giersch, A. (2023). Dopamine precursor depletion affects performance and confidence judgements when events are timed from an explicit, but not an implicit onset. *Scientific Reports*, *13*(1), 21933. https://doi.org/10.1038/s41598-023-47843-w

Kanai, R., Paffen, C. L. E., Hogendoorn, H., & Verstraten, F. A. J. (2006). Time dilation in dynamic visual display. *Journal of Vision*, *6*(12), 8. https://doi.org/10.1167/6.12.8

Kane, L. S., & Lown, B. A. (1986). Stevens' Power Law and Time Perception: Effect of Filled Intervals, Duration of the Standard, and Number of Presentations of the Standard. *Perceptual and Motor Skills*, *62*(1), 35-38. https://doi.org/10.2466/pms.1986.62.1.35

Kawahara, H., & Yotsumoto, Y. (2020). Multiple Irrelevant Duration Information Affects the Perception of Relevant Duration Information: Interference With Selective Processing of Duration. *i-Perception*, *11*(6), 3-8. https://doi.org/10.1177/2041669520973223

Killeen, P. R., & Taylor, T. J. (2000). How the propagation of error through stochastic counters affects time discrimination and other psychophysical judgments. *Psychological Review*, *107*(3), 430-459. https://doi.org/10.1037/0033-295X.107.3.430

Kingdom, F. A. A., & Prins, N. (2016). Psychophysics: A Practical Introduction: Second Edition. En *Psychophysics: A Practical Introduction: Second Edition*. https://doi.org/10.1016/C2012-0-01278-1

Kladopoulos, C. N., Brown, B. L., Hemmes, N. S., & De Vaca, S. C. (1998). The start-stop procedure: Estimation. *Perception & Psychophysics*, *60*(3), 438-450. https://doi.org/10.3758/BF03206865

Knill, D. C., & Richards, W. (Eds.). (1996). *Perception as Bayesian Inference* (1.ª ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511984037

Laera, G., Brummer, J., Hering, A., Kliegel, M., & Horn, S. (2024). The cost of monitoring in time-based prospective memory. *Scientific Reports*, *14*(1), 2279. https://doi.org/10.1038/s41598-024-52501-w

Lamotte, M., Droit-Volet, S., & Izaute, M. (2017). Confidence judgment in a temporal generalization task: Accuracy and sensitivity to task difficulty. *L'Année Psychologique*, *Vol. 117*(3), 275-298. https://doi.org/10.3917/anpsy.173.0275

Linares, D., Aguilar-Lleyda, D., & López-Moliner, J. (2019). Decoupling sensory from decisional choice biases in perceptual decision making. *eLife*, *8*, e43994. https://doi.org/10.7554/eLife.43994

Linares, D., & López-Moliner, J. (2016). Quickpsy: An R Package to Fit Psychometric Functions for Multiple Groups. *The R Journal*, *8*(1), 122-131. https://doi.org/10.32614/RJ-2016-008

Maarseveen, J., Hogendoorn, H., Verstraten, F. A. J., & Paffen, C. L. E. (2017). An investigation of the spatial selectivity of the duration after-effect. *Vision Research*, *130*, 67-75. https://doi.org/10.1016/j.visres.2016.11.003

Maarseveen, J., Paffen, C. L. E., Verstraten, F. A. J., & Hogendoorn, H. (2019). The duration aftereffect does not reflect adaptation to perceived duration. *PLoS ONE*, *14*(3), 1-11. https://doi.org/10.1371/journal.pone.0213163

Malapani, C., & Fairhurst, S. (2002). Scalar Timing in Animals and Humans. *Learning and Motivation*, *33*(1), 156-176. https://doi.org/10.1006/lmot.2001.1105

Matell, M. S., & Meck, W. H. (2000). Neuropsychological mechanisms of interval timing behavior. *BioEssays*, *22*(1), 94-103. https://doi.org/10.1002/(SICI)1521-1878(200001)22:1<94::AID-BIES14>3.0.CO;2-E

Matell, M. S., & Meck, W. H. (2004). Cortico-striatal circuits and interval timing: Coincidence detection of oscillatory processes. *Cognitive Brain Research*, *21*(2), 139-170. https://doi.org/10.1016/j.cogbrainres.2004.06.012

Matthews, W. J. (2013). How does sequence structure affect the judgment of time? Exploring a weighted sum of segments model. *Cognitive Psychology*, *66*(3), 259-282. https://doi.org/10.1016/j.cogpsych.2013.01.001

Matthews, W. J., & Meck, W. H. (2016). Temporal cognition: Connecting subjective time to perception, attention, and memory. *Psychological Bulletin*, *142*(8), 865-907. https://doi.org/10.1037/bul0000045

Merchant, H., & De Lafuente, V. (Eds.). (2014). *Neurobiology of Interval Timing* (Vol. 829). Springer New York. https://doi.org/10.1007/978-1-4939-1782-2

Miall, C. (1989). The Storage of Time Intervals Using Oscillating Neurons. *Neural Computation*, *1*(3), 359-371. https://doi.org/10.1162/neco.1989.1.3.359

Morgan, M. J., Giora, E., & Solomon, J. A. (2008). A single "stopwatch" for duration estimation, A single "ruler" for size. *Journal of Vision*, *8*(2), 14. https://doi.org/10.1167/8.2.14

Ono, F., & Kawahara, J.-I. (2007). The subjective size of visual stimuli affects the perceived duration of their presentation. *Perception & Psychophysics*, *69*(6), 952-957. https://doi.org/10.3758/BF03193932

Oprisan, S. A., & Buhusi, C. V. (2011). Modeling Pharmacological Clock and Memory Patterns of Interval Timing in a Striatal Beat-Frequency Model with Realistic, Noisy Neurons. *Frontiers in Integrative Neuroscience*, *5*. https://doi.org/10.3389/fnint.2011.00052

Oprisan, S. A., Novo, D., Buhusi, M., & Buhusi, C. V. (2022). Resource Allocation in the Noise-Free Striatal Beat Frequency Model of Interval Timing. *Timing & Time Perception*, *11*(1-4), 103-123. https://doi.org/10.1163/22134468-bja10056

O'Toole, B., & Wenderoth, P. (1977). The tilt illusion: Repulsion and attraction effects in the oblique meridian. *Vision Research*, *17*(3), 367-374. https://doi.org/10.1016/0042-6989(77)90025-6

Parkinson, C., Liu, S., & Wheatley, T. (2014). A Common Cortical Metric for Spatial, Temporal, and Social Distance. *The Journal of Neuroscience*, *34*(5), 1979-1987. https://doi.org/10.1523/JNEUROSCI.2159-13.2014

Peirce, J. W. (2007). PsychoPy—Psychophysics software in Python. *Journal of neuroscience methods*, *162*(1-2), 8-13.

Prins, N., & Kingdom, F. A. A. (2018). Applying the Model-Comparison Approach to Test Specific Research Hypotheses in Psychophysical Research Using the Palamedes Toolbox. *Frontiers in Psychology*, *9*, 1250. https://doi.org/10.3389/fpsyg.2018.01250

R Core Team. (2020). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing. http://www.r-project.org/

Rakitin, B. C., Gibbon, J., Penney, T. B., Malapani, C., Hinton, S. C., & Meck, W. H. (1998). Scalar expectancy theory and peak-interval timing in humans. *Journal of Experimental Psychology: Animal Behavior Processes*, *24*(1), 15-33. https://doi.org/10.1037/0097-7403.24.1.15

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59-108. https://doi.org/10.1037/0033-295X.85.2.59

Ratcliff, R., & McKoon, G. (2008). The Diffusion Decision Model: Theory and Data for Two-Choice Decision Tasks. *Neural Computation*, *20*(4), 873-922. https://doi.org/10.1162/neco.2008.12-06-420

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion Decision Model: Current Issues and History. *Trends in Cognitive Sciences*, *20*(4), 260-281. https://doi.org/10.1016/j.tics.2016.01.007

Rattat, A., & Droit-Volet, S. (2012). What is the best and easiest method of preventing counting in different temporal tasks? *Behavior Research Methods*, *44*(1), 67-80. https://doi.org/10.3758/s13428-011-0135-3

Roberts, B., Harris, M. G., & Yates, T. A. (2005). The roles of inducer size and distance in the Ebbinghaus illusion (Titchener circles). *Perception*, *34*(7), 847-856. https://doi.org/10.1068/p5273

Roberts, S. (1981). Isolation of an internal clock. *Journal of Experimental Psychology: Animal Behavior Processes*, 7(3), 242-268. https://doi.org/10.1037/0097-7403.7.3.242

Shi, Z., Church, R. M., & Meck, W. H. (2013). Bayesian optimization of time perception. *Trends in Cognitive Sciences*, *17*(11), 556-564. https://doi.org/10.1016/j.tics.2013.09.009

Sima, S., & Sanayei, M. (2024). Same principle, but different computations in representing time and space. *Frontiers in Neuroscience*, *18*, 1387641. https://doi.org/10.3389/fnins.2024.1387641

Simen, P., Balci, F., DeSouza, L., Cohen, J. D., & Holmes, P. (2011). A model of interval timing by neural integration. *Journal of Neuroscience*, *31*(25), 9238-9253. https://doi.org/10.1523/JNEUROSCI.3121-10.2011

Simen, P., Vlasov, K., & Papadakis, S. (2016). Scale (In)variance in a unified diffusion model of decision making and timing. *Psychological Review*, *123*(2), 151-181. https://doi.org/10.1037/rev0000014

Skagerlund, K., Karlsson, T., & Träff, U. (2016). Magnitude processing in the brain: An fMRI study of time, space, and numerosity as a shared cortical system. *Frontiers in Human Neuroscience*, *10*(OCT2016), 1-12. https://doi.org/10.3389/fnhum.2016.00500

Stevens, S. (1957). On the Psychophysical Law. *PSYCHOLOGICAL REVIEW*, *64*(3), 153-181. https://doi.org/10.1037/h0046162

Titchener, E. B. (1901). *Experimental psychology: A manual of laboratory practice, vol. I: Qualitative experiments*. New York: The Macmillan Company.

Tobin, S., Bisson, N., & Grondin, S. (2010). An Ecological Approach to Prospective and Retrospective Timing of Long Durations: A Study Involving Gamers. *PLoS ONE*, *5*(2), e9271. https://doi.org/10.1371/journal.pone.0009271

Tobin, S., & Grondin, S. (2012). Time perception is enhanced by task duration knowledge: Evidence from experienced swimmers. *Memory & Cognition*, *40*(8), 1339-1351. https://doi.org/10.3758/s13421-012-0231-3

Treisman, M. (1963). Temporal discrimination and the indifference interval: Implications for a model of the «internal clock». *Psychological Monographs: General and Applied*, *77*(13), 1-31. https://doi.org/10.1037/h0093864

Unity 2020.3.27f1. (2020). [Software]. Unity Technologies. https://unity.com/

van Rijn, H., & Taatgen, N. A. (2008). Timing of multiple overlapping intervals: How many clocks do we have? *Acta Psychologica*, *129*(3), 365-375. https://doi.org/10.1016/j.actpsy.2008.09.002

Vatakis, A., Balcı, F., Di Luca, M., & Correa, Á. (2018). Timing and Time Perception: Procedures, Measures, & Applications. En *Timing and Time Perception: Procedures, Measures, & Applications*. BRILL. https://doi.org/10.1163/9789004280205

Walsh, V. (2003). A theory of magnitude: Common cortical metrics of time, space and quantity. *Trends in Cognitive Sciences*, *7*(11), 483-488. https://doi.org/10.1016/j.tics.2003.09.002

Wearden, J. (2016). The Psychology of Time Perception. En *The Psychology of Time Perception*. Palgrave Macmillan UK. https://doi.org/10.1057/978-1-137-40883-9

Wearden, J. H. (2023). Vierordt's Law for Space and Time: Hollingworth (1909) and "The Law of Central Tendency". *Timing & Time Perception*, *12*(1), 5-14. https://doi.org/10.1163/22134468-bja10082

Wearden, J. H., & Lejeune, H. (2008). Scalar Properties in Human Timing: Conformity and Violations. *Quarterly Journal of Experimental Psychology*, *61*(4), 569-587. https://doi.org/10.1080/17470210701282576

Wehrman, J. J., Wearden, J., & Sowman, P. (2020). Decisional carryover effects in interval timing: Evidence of a generalized response bias. *Attention, Perception, & Psychophysics*, *82*(4), 2147-2164. https://doi.org/10.3758/s13414-019-01922-1

Wichmann, F. A., & Hill, N. J. (2001). The psychometric function: I. Fitting, sampling, and goodness of fit. *Perception & Psychophysics*, *63*(8), 1293-1313. https://doi.org/10.3758/BF03194544

Wiener, M., Thompson, J. C., & Coslett, H. B. (2014). Continuous Carryover of Temporal Context Dissociates Response Bias from Perceptual Influence for Duration. *PLoS ONE*, *9*(6), e100803. https://doi.org/10.1371/journal.pone.0100803

Zakay, D. (2015). The temporal-relevance temporal-uncertainty model of prospective duration judgment. *Consciousness and Cognition*, *38*, 182-190. https://doi.org/10.1016/j.concog.2015.10.006

Zakay, D., & Block, R. A. (1997). Temporal Cognition. *Current Directions in Psychological Science*, *6*(1), 12-16. https://doi.org/10.1111/1467-8721.ep11512604

Zhou, J., Duong, L. R., & Simoncelli, E. P. (2024). A unified framework for perceived magnitude and discriminability of sensory stimuli. *Proceedings of the National Academy of Sciences*, *121*(25), e2312293121. https://doi.org/10.1073/pnas.2312293121

ANNEXES

LIST OF FIGURES

LIST OF TABLES

LIST OF FORMULAS

FRONT PAGES

STUDY 1

www.nature.com/scientificreports

scientific reports

OPEN

Duration judgments are mediated by the similarity with the temporal context

Jaume Boned & Joan López-Moliner

When we try to assess the duration of an event, we are often affected by external information. Studies on multiple timing have found that simultaneous timing information can produce an averaging or central tendency effect, where the perceived duration of the elements tends to be biased towards a general average. We wanted to assess how this effect induced by simultaneous distractors could depend on the temporal similarity between stimuli. We used a duration judgment task in which participants (n = 22) had to compare the duration of two identical targets (1 s) accompanied by simultaneous distractors of different durations (0.3, 0.7, 1.5 or 3 s). We found a central tendency effect, where duration judgments of the target were systematically biased towards the duration of the distractors that accompanied them. We put forward a model based on the concept of duration-channels that can explain the central tendency effect with only one estimated parameter. This parameter modulates the rate of decay of this effect as distractors duration become more different than the duration of the target.

Perceiving the duration of the events around us is a key component of how we experience the world. Research in time perception has focused on many factors that can make an event seem to last longer or shorter[1–4]. However, distortions of duration can be caused not only by the intrinsic properties of such events but also by the presence of external but concurrent stimulation. In real-life situations, events are not quite isolated in the temporal dimension. When we attend to some event that is taking place during a specific time interval, other events can often occur simultaneously in the same scene. The durations of these concurrent events are potential sources of perceptual noise that can affect how we experience the duration of the main event we are trying to focus on[1,5,6]. This concurrent information, referred to as the temporal context, includes all that temporal information in the same environment as the event to be perceived. For example, the duration of a red traffic light for which we are waiting might not be perceived as lasting the same when isolated as when there are many other traffic lights constantly changing at their own pace for different lanes.

Therefore, this temporal context can refer to simultaneous information about time such as duration, frequency, or synchrony to other surrounding elements and to previously, or even posteriorly, experienced information related to that same event.

To begin with, studies focusing on the contextual effects of preceding information proved that our estimations are not independent of previously presented information. For example, Hallez et al.[7] studied the impact of temporal context on a temporal reproduction task. Under the Bayesian theory of perceptual inference of time, they expected that reproductions of duration could be affected by previous experience (prior) with different durations. Specifically, they found that reproductions of the same duration tended to be overestimated when presented in an array of stimuli with longer durations and underestimated when such array was of shorter durations. They suggested that as compensation when facing uncertainty, time reproductions relied more on prior information, which induced a central tendency effect in which estimations were averaged towards the values of its temporal context[6,7].

The same result is usually found in "carryover effect" studies on duration judgments[8], but more importantly, these effects include the influence of both previously presented stimuli and previous decisions. Interestingly, the direction of this effect is shifted between decisional and perceptual carryover. For example, central tendency or assimilative effects are usually found from previous duration judgments, whilst previously presented durations can produce a repulsion effect, where current durations are perceived as more different in magnitude than previously presented stimuli[8,9].

Vision and Control of Action (VISCA) Group, Department of Cognition, Development and Psychology of Education, Institut de Neurociències, Universitat de Barcelona, Barcelona, Catalonia, Spain. email: j.lopezmoliner@ub.edu

Scientific Reports | (2022) 12:22575 | https://doi.org/10.1038/s41598-022-27168-w nature portfolio 1

STUDY 3

Standard Article

i-PERCEPTION

i-Perception
2024, Vol. 15, 1–18

DOI: 10.1177/20416695241279675
journals.sagepub.com/home/ipe
Sage

Quantifying uncertainty in time perception: A modified reproduction method

Jaume Boned and Joan López-Moliner
Institut de Neurociències, Universitat de Barcelona, Barcelona, Spain

Abstract
In time perception research, we typically measure how an observer perceives time intervals by collecting data from multiple trials with a single estimate recorded on each. However, this gives us limited information about the observer's uncertainty for each estimate, which we usually measure from the variability across trials. Our study tested the potential of a modified reproduction task to provide a duration estimate as well as a measure of uncertainty on a single-trial basis. Participants were instructed to press and hold a key to temporally bracket the end of a learned duration (0.6–4 s) as narrowly as possible. Therefore, we expected the bracket's length to indicate the level of uncertainty. We compared this method to a conventional reproduction task. Taking the mid-point of the bracket as the duration estimate, we found that both methods produced equivalent data. Critically, the bracket length predicted reproduction variability, indicating that a single bracket obtained in an individual trial could potentially provide as much information as multiple reproductions. Additionally, relative variability in bracket start and end positions suggests a combination of additive and multiplicative noise components. Our findings highlight the bracket method as a more efficient and nuanced approach to measure time estimates and their associated uncertainty, expanding the methodological toolkit and opening new avenues in time perception research.

Keywords
time perception, reproduction, uncertainty, quantitative timing, time estimation

Date received: 19 March 2024; accepted: 15 August 2024

The study of time perception plays a critical role in understanding human cognition and behavior. It aims to shed light on how individuals measure, interpret, and interact with the temporal aspects of their environment, making it a pivotal aspect of our daily life. For this reason, using adequate methods for measuring time perception is essential to this field.

Corresponding author:
Jaume Boned, Vision and Control of Action (VISCA) Group, Department of Cognition, Development and Psychology of Education, Institut de Neurociències, Universitat de Barcelona, Barcelona, Catalonia, Spain.
Email: jaumebonedgarau@gmail.com