



UNIVERSITÀ
DEGLI STUDI
FIRENZE

DOTTORATO TOSCANO IN NEUROSCIENZE

CICLO XXXVII

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The dynamics of time perception: exploring the cognitive and motor contributions to temporal estimation

Settore Scientifico Disciplinare M-PSI/02

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Anni 2021/2024

SUMMARY

Time perception, a fundamental aspect of human cognition, has been the focus of extensive research due to its significant role in shaping behavior and interaction with the world. The ability to perceive and estimate time is influenced by a complex interplay of factors including cognitive load, task complexity, and the allocation of attentional resources. In the broader literature, models such as the Scalar Expectancy Theory and Internal Clock Models have sought to explain time perception through internal processes involving the brain's mechanisms for accumulating temporal information. These models suggest that our sense of time is affected by various cognitive and contextual factors, with changes in attention and cognitive demands leading to distortions in time perception.

The studies discussed here contribute to this body of research by exploring how different cognitive and motor tasks influence time estimation. While the literature commonly focuses on cognitive load and its impact on temporal judgments, these studies delve deeper into the effects of task complexity and the combination of motor activities with cognitive tasks. Previous findings have shown that higher cognitive loads tend to shorten perceived time intervals, aligning with the attentional allocation model, which posits that the distribution of attentional resources plays a key role in shaping our perception of time.

These studies offer new perspectives by examining time estimation without fixed intervals and by comparing different types, complexity and difficulty of tasks. Findings suggest that the interaction between cognitive load and motor tasks leads to a consistent underestimation of time, particularly when cognitive complexity increases. In contrast, purely motor tasks seem to have a more limited influence on time perception, highlighting the primacy of cognitive demands in shaping how time is experienced. The distinction between visual and executive tasks also suggests that different types of cognitive processes modulate time perception in unique ways, with tasks more complex, that engage working memory and executive functions, like mathematical tasks, resulting in more pronounced underestimations of time than those involving visual processing. Together, these studies enrich the existing literature by offering nuanced insights into how cognitive and motor tasks interact to influence temporal perception, broadening our current understanding and offering new insights into the cognitive and neural mechanisms underpinning how we perceive and estimate time.

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Publications

- Castellotti S, D'Agostino O, Biondi A, Pignatiello L, Del Viva MM. Influence of Motor and Cognitive Tasks on Time Estimation. *Brain Sci.* 2022 Mar 18;12(3):404.
- D'Agostino O, Castellotti S and Del Viva MM (2023) Time estimation during motor activity. *Front. Hum. Neurosci.* 17:1134027. doi: 10.3389/fnhum.2023.1134027.

Declaration

I, the author, declare that the work presented in this thesis is my own and has not been submitted for a degree at any other institution.

Chapter 1

TIME PERCEPTION

1. Introduction

1.1 Theoretical foundations of time perception

Time perception is a complex cognitive function that enables individuals to estimate durations, sequence events, and synchronize their actions with the environment (Sucala et al., 2010). Several theoretical models have been developed to explain how humans perceive time, each emphasizing different aspects of this intricate process. From internal clock mechanisms to attentional allocation and contextual influences, these models offer a comprehensive understanding of the factors that shape our temporal judgments (Allman et al., 2014; Buhsu & Meck, 2005; Gibbon, 1977; Grondin, 2010; Matthews & Meck, 2014).

One of the foundational theories in time perception literature is the Scalar Expectancy Theory (SET, (Gibbon, 1977; J. H. Wearden, 1999)). This model posits that individuals perceive time through an internal clock system consisting of a pacemaker, which emits pulses at a regular rate. These pulses are accumulated by a counter, and the total number of pulses determines the perceived duration of an interval. The variability in time perception is attributed to the inherent noise in the pacemaker's rate, as well as the processes of encoding, storing, and retrieving temporal information (**Figure 1**). Although SET has provided valuable insights into the basic mechanisms of time estimation, it has been criticized for its overly mechanistic view and its inability to fully account for the influence of attention, motor activity, and sensory input on temporal judgments.

To address the limitations of purely clock-based models, attentional theories of time perception, such as the attentional allocation model, have been developed (Macar et al., 1994a; Zakay & Block, 1996). These models emphasize the role of attention in modulating time perception. According to this model, the internal pacemaker generates pulses that are counted to estimate duration, but an attentional gate regulates the flow of these pulses into the accumulator. When more attention is directed toward the passage of time, the gate remains open longer, allowing more pulses to be accumulated and resulting in a longer perceived duration. Conversely, when attention is diverted to non-temporal tasks, fewer pulses are counted, leading to an underesti-

mation of time. This dynamic interplay between attentional resources and time perception explains why time seems to pass quickly during engaging activities and slowly during periods of boredom (for a review, see (Grondin, 2010; Matthews & Meck, 2014, 2016)).

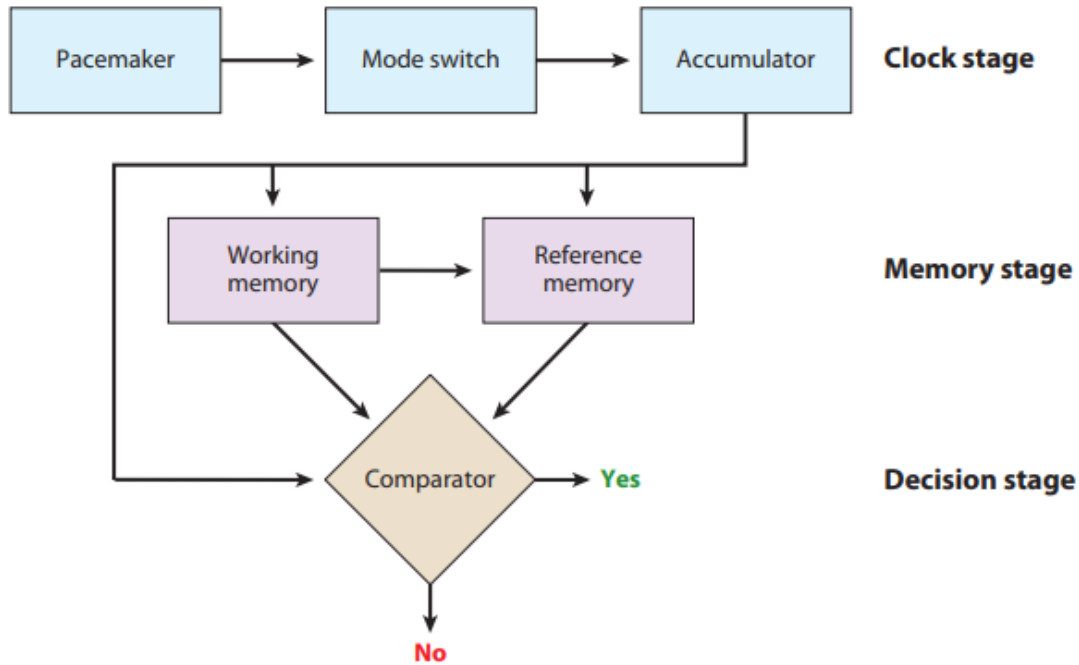


Figure 1. Model of internal clock. The information-processing model of interval timing as specified by scalar timing theory and other internal clock theories of psychological time, by Allman and colleagues (2014, (Allman et al., 2014)).

Time perception is also influenced by the context in which temporal judgments are made. Contextual factors, such as the predictability of events, the sensory modality through which time is experienced, and the surrounding temporal intervals, all play a significant role in shaping perceived durations (Droit-Volet & Meck, 2007; John H Wearden, 2003). For example, research has shown that auditory stimuli are often perceived as longer than visual stimuli of the same duration, suggesting that time perception varies across sensory modalities (Goldstone & Lhamon, 1974). This finding highlights the need to consider how different types of sensory information are processed by the brain when estimating time. Additionally, the influence of sensory modality varies depending on the temporal scale of the interval. For short durations, typically less than a second, the precision of temporal judgments is strongly linked to the modality of the stimulus, with auditory stimuli consistently yielding more precise and less variable time estimates compared to visual or tactile stimuli, due to the auditory system's superior

temporal resolution. This modality-specific difference is largely attributed to the superior temporal resolution of the auditory system, which allows for finer discrimination of temporal intervals. However, for longer durations, spanning several seconds or more, cognitive factors such as attention, memory, and context play a dominant role, reducing the influence of sensory inputs (Block & Zakay, 2010; Wittmann, 2009). One important factor that influences time perception is the central tendency effect, which causes people to overestimate shorter time intervals and underestimate longer ones (Gu & Meck, 2011; Jazayeri & Shadlen, 2010). This phenomenon can be understood through Bayesian models, which suggest that time judgments are not only based on immediate sensory information but are also shaped by the statistical patterns of previously encountered durations (Jazayeri & Shadlen, 2010; Mamassian et al., 2002; Shi & Burr, 2016). Other contextual elements, such as the familiarity and quantity of stimuli, also play a role in shaping time perception (R. A. Block et al., 2010). For instance, when stimuli within a time interval is less familiar, they are perceived as lasting longer, as they demand more cognitive resources to process. Moreover, the perceived duration of an interval increases as the number of stimuli within it grows (Schiffman, 1977).

Moreover, the temporal context in which events occur can significantly affect time perception. When intervals are embedded within predictable patterns, individuals are more accurate in their time estimations compared to when intervals are random or unpredictable (Jones & Mcauley, 2005). This suggests that the brain integrates contextual information to create a coherent temporal experience, rather than relying solely on an internal clock. Repetition and predictability of events also enhance temporal accuracy, as individuals become able to synchronize their internal timing mechanisms with external rhythms. The role of predictability is also reflected in studies involving motor synchronization tasks, where predictable rhythms enable individuals to fine-tune their motor responses and enhance the precision of their temporal estimates (Repp & Su, 2013). Such findings underline the dynamic interplay between external temporal patterns and internal timing mechanisms.

The integration of motor activity into models of time perception has gained increasing attention in recent research. Rather than viewing time perception as a purely cognitive process, studies have shown that motor systems play a crucial role in shaping temporal judgments

(Castellotti et al., 2022; D'Agostino et al., 2023; Kroger-Costa et al., 2013). The embodied cognition framework posits that cognitive processes, including time perception, are grounded in bodily actions and sensorimotor experiences. This perspective suggests that motor activity can modulate time perception by either compressing or expanding perceived durations, depending on the nature of the movement and the level of motor engagement (Wilson, 2008). For example, repetitive motor actions, such as tapping or walking, often lead to temporal distortions, with overestimation of short intervals and underestimation of longer intervals (Gilden & Marusich, 2009). Similarly, motor tasks requiring fine coordination and precision, such as playing an instrument, are associated with heightened temporal accuracy, reflecting the close link between motor control and internal timing mechanisms (Ivry & Spencer, 2004).

Overall, time perception emerges as a multifaceted process influenced by internal mechanisms, such as the pacemaker-accumulator system, and external factors, including attention, sensory input, and environmental context. Attention-based models emphasize the dynamic allocation of cognitive resources during temporal estimation, while contextual models highlight the importance of external stimuli and temporal patterns. Motor activity further complicates this picture by interacting with cognitive and sensory processes to shape our experience of time. Recent research has also emphasized the need to consider how different time scales influence the relative contribution of these factors. For instance, while internal clock mechanisms play a predominant role in short-interval timing, cognitive resources, and contextual integration are crucial for longer intervals, reflecting the adaptability of temporal processing across varying durations (Coull et al., 2015; Ivry & Schlerf, 2008).

Furthermore, a substantial body of research on human time perception has primarily focused on the estimation of brief time intervals, typically ranging from 10 to 100 milliseconds or extending to several seconds (Buhusi & Meck, 2005; Grondin, 2010; Ivry & Schlerf, 2008; Matthews & Meck, 2014; Wittmann, 2009). These studies have provided valuable insights into how people perceive and estimate short durations, revealing much about the mechanisms underlying temporal processing in these intervals. For instance, Wittmann (2009) extensively reviewed the inner experience of time, emphasizing that much of the research has concentrated on short-duration intervals and their neural correlates. According to Wittmann, this focus has

elucidated how the brain encodes and processes very brief temporal events, shedding light on the internal sense of time over milliseconds to seconds (Wittmann, 2009). Nevertheless, studies focusing on sub-second durations often overlook how these processes extend to longer intervals. The relative paucity of research on time spans extending into minutes highlights a critical gap in the literature, as temporal judgments over longer durations are more heavily reliant on reconstructive processes, memory, and contextual integration (Politi et al., 2018). As research continues to explore these interconnections, it becomes clear that time perception is not a uniform or static process but a highly adaptable and context-dependent function of the brain.

However, there is a notable gap in the literature regarding temporal estimations of longer intervals, specifically those in the range of minutes. While brief time intervals have been thoroughly investigated, fewer studies have addressed how individuals perceive and estimate durations that extend into the minutes (Politi et al., 2018). This gap is significant because understanding how people process longer time spans is crucial for comprehending the full spectrum of time perception and its implications for various cognitive and behavioral functions. Ivry and Schlerf (2008) contribute to this discussion highlighting that while dedicated models propose specialized neural mechanisms for processing time, intrinsic models suggest that time perception is a byproduct of general cognitive processes (Ivry & Schlerf, 2008). Both models primarily focus on short intervals, thus leaving the exploration of longer durations relatively underexplored. Ivry and Schlerf's work underscores the need for further research into how these models can be extended to understand the perception of longer time intervals. The relative paucity of research on time intervals extending to minutes means that our understanding of long-duration time perception remains limited. In summary, while extensive research has elucidated the mechanisms behind brief time intervals, there remains a significant need for studies investigating temporal estimations of longer durations. Addressing this gap will enhance our understanding of time perception across a wider range of time scales and provide a more complete picture of how temporal processing influences human cognition and behavior in everyday life situations.

1.2 Neurobiological mechanisms of time perception

The neurobiological mechanisms underlying time perception encompass a complex network of brain regions that contribute to different aspects of temporal processing, from time generation and accumulation to decision-making based on temporal estimates. This intricate system spans across structures such as the basal ganglia, cerebellum, prefrontal cortex, and supplementary motor area, with recent studies illuminating the unique contributions of these areas. One foundational study by Coull, Nobre, and Frith (2004) explored the neuroanatomical basis of time perception and identified the basal ganglia and cerebellum as core regions. Through functional MRI, they found that these structures play crucial roles in the “internal clock” mechanism, with the basal ganglia involved in time interval generation and the cerebellum supporting precision in temporal estimates (Coull et al., 2004). Merchant et al. (2013) expanded on this understanding by showing that the basal ganglia and cerebellum are consistently activated across different timing tasks, whether perceptual or motor. Their study reinforced the idea that time perception does not rely on a single structure but rather on a broad network that adapts based on the task demands. They highlighted that the right parietal cortex also plays a significant role in time estimation, particularly in tasks involving higher-order cognitive processes, pointing to the role of a distributed temporal processing network that includes both cognitive and sensory components (Merchant et al., 2013). Further, Lewis and Miall (2003) contributed to this model by distinguishing the roles of the prefrontal cortex in time perception, showing that its involvement is modulated by cognitive load. Their fMRI research found that the prefrontal cortex is particularly active when participants are tasked with time estimation under high cognitive demands, such as in complex mathematical or executive tasks, where attentional resources are heavily taxed. This suggests that the prefrontal cortex may serve to manage attentional resources during tasks that require sustained attention to time (Lewis & Miall, 2003).

An interesting study by Buetti et al. (2008) explored the neural mechanisms underlying motor and perceptual representations of temporal intervals. Their research identified distinct brain circuits for these two types of temporal processing, indicating that while motor timing tasks

engage areas associated with action planning and execution, perceptual timing relies on circuits involved in sensory processing. This distinction highlights how the brain organizes temporal information differently based on the nature of the task, suggesting specialized roles for specific brain regions in timing (**Figure 2**, (Buetti et al., 2008)). Moreover, Wittmann (2009) reviewed the role of the insula in time perception, emphasizing its involvement in the subjective experience of time. The insula is often associated with interoceptive awareness, which contributes to the subjective sense of the passage of time. Wittmann suggested that the insula may function as a bridge between physiological states and temporal perception, linking emotional and bodily awareness with time experience. This aligns with studies showing that heightened emotional states, which activate the insula, can distort time perception (Wittmann, 2009). Grondin (2010) also highlights the cerebellum's role in precise timing for short intervals, particularly in sensorimotor synchronization tasks like rhythmic tapping. In contrast, the basal ganglia are critical for modulating the pacemaker-accumulator system proposed by Scalar Expectancy Theory (Gibbon, 1977). Dopaminergic modulation within the basal ganglia influences the rate of pulse generation, which explains how fluctuations in dopamine levels can accelerate or decelerate perceived time, as observed in clinical conditions such as Parkinson's disease (Grondin, 2010). Additionally, the dorsolateral prefrontal cortex and SMA are implicated in tasks requiring attentional control, with the SMA specifically involved in initiating and monitoring temporal sequences (Lewis & Miall, 2003; Coull et al., 2004). Hayashi et al. (2018) investigated the neural representations of time in the human frontoparietal cortex, emphasizing its role in temporal processing. Their findings indicate that this region integrates sensory and cognitive information to construct temporal intervals, supporting both perceptual and executive functions in timing tasks (Hayashi et al., 2018). The study highlights the dynamic interplay between different areas of the frontoparietal cortex, reinforcing the idea that time perception is a distributed process involving various cognitive functions. These studies form a growing body of literature that has established time perception as a multifaceted and distributed function rather than a localized process.

Additional studies like those by Gibbon (1977) and Wearden (2003) contributed theoretical models such as the scalar timing theory, which posits that time perception involves an internal

clock with a “switch” that opens or closes depending on the attention directed toward the timing task. This mechanism, they suggest, is modulated by cognitive load and attention, with areas like the pre-SMA and dorsolateral prefrontal cortex implicated in opening this “switch” during tasks requiring focused temporal attention.

Together, these studies indicate that time perception depends on an adaptable and task-sensitive neural network, spanning the basal ganglia, cerebellum, prefrontal cortex, insula, SMA, and sensory cortices. This network is flexibly engaged depending on whether a task is motor or perceptual, simple or complex, and reflects how cognitive load, emotional state, and sensory input interact to shape our perception of time. This extensive system underscores the importance of considering time perception within the broader context of cognitive, motor, and emotional processes, providing valuable insights for fields like human-computer interaction, clinical psychology, and cognitive rehabilitation.

(A – CA) – (P – CP)

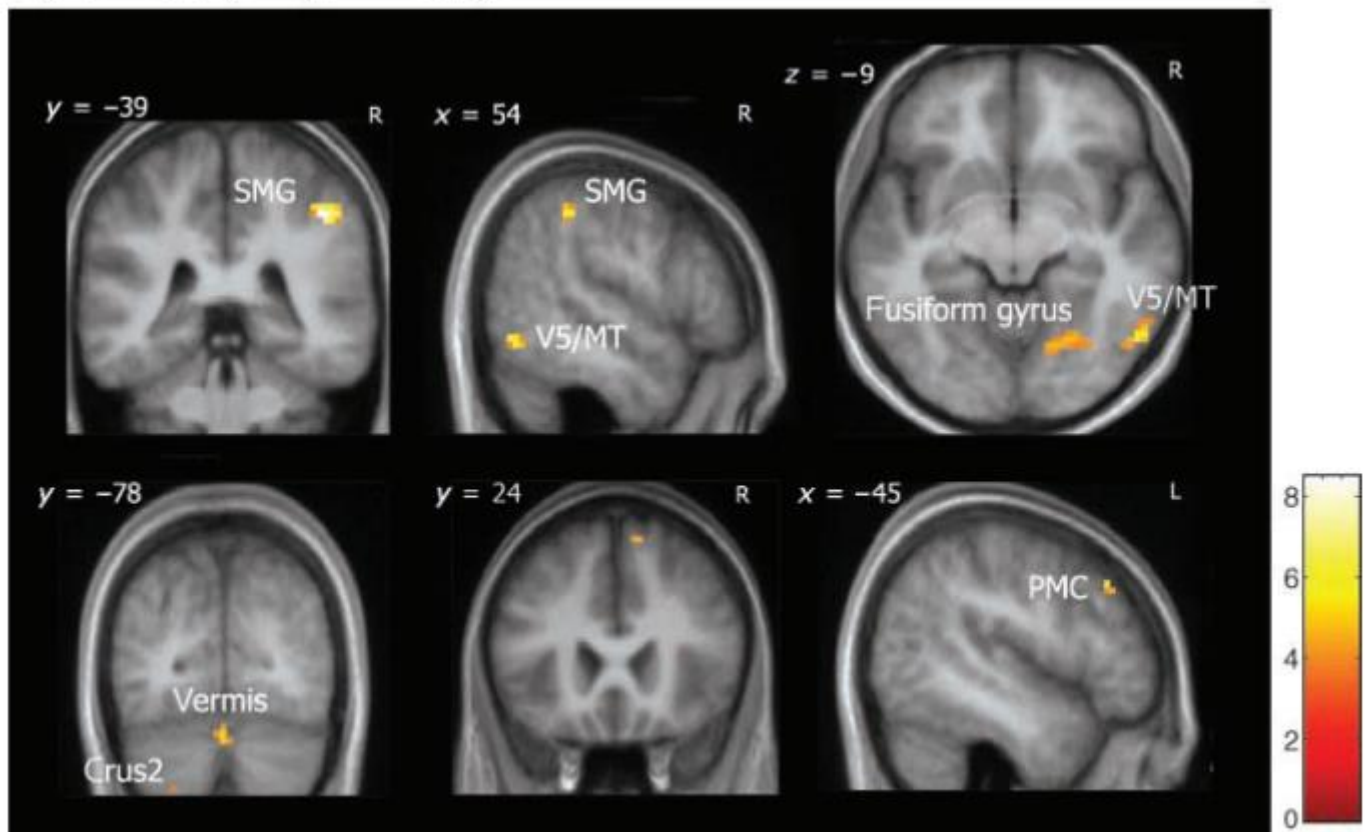


Figure 2. Neural substrates of time perception. *Loci activated by the statistical contrast (A-CA)- (P-CP) overlaid on the average T1-weighted structural image from the 14 subjects in the stereotactic space of Talairach and Tournoux (1988). This contrast shows brain areas where the reproduction task (vs. its control) evoked significantly more activity than the estimation task (vs. its control). Activations were found in the right supramarginal gyrus (SMG), right V5/MT, left fusiform gyrus, cerebellar vermis (all significant $p < .05$, corrected at cluster level), left middle frontal gyrus, right pre-SMA, left premotor cortex, left SMG, bilateral cerebellum (left crus2 and right VIII lobule, all significant $p < .001$, uncorrected, (Bueti et al., 2008)).*

1.3 Physiological and emotional modulators of time perception

The perception of time is deeply intertwined with our emotional states, with different emotions leading to the dilation or compression of perceived time. The subjective experience of time is not a fixed phenomenon but one that can be significantly modulated by various internal and external factors. Among these, emotional arousal has been shown to play a particularly pivotal role, with emotions such as fear, anxiety, excitement, and even boredom altering how we perceive the passage of time. A growing body of research has investigated these links, revealing how both arousal levels and valence (whether an emotion is positive or negative) contribute to the dynamics of time perception.

One of the most influential frameworks explaining this relationship is the Arousal/Valence Model, proposed by Droit-Volet and Meck (2007). According to this model (Droit-Volet & Meck, 2007), the perception of time is closely linked to emotional arousal and valence. High-arousal states, such as fear or excitement, tend to accelerate the rate of the internal clock, leading to what is known as time dilation, where events are perceived as lasting longer than they actually do. Conversely, low-arousal emotional states, such as boredom or contentment, can slow down the internal clock, resulting in time compression, where events seem to pass more quickly than they truly are (Droit-Volet & Meck, 2007). For example, in an experiment by Gil and Droit-Volet (2011), participants were exposed to fear-inducing stimuli and they overestimated time intervals compared to those exposed to neutral or happy stimuli, reinforcing the connection between fear and time dilation (**Figure 3**, (Gil & Droit-Volet, 2012)).

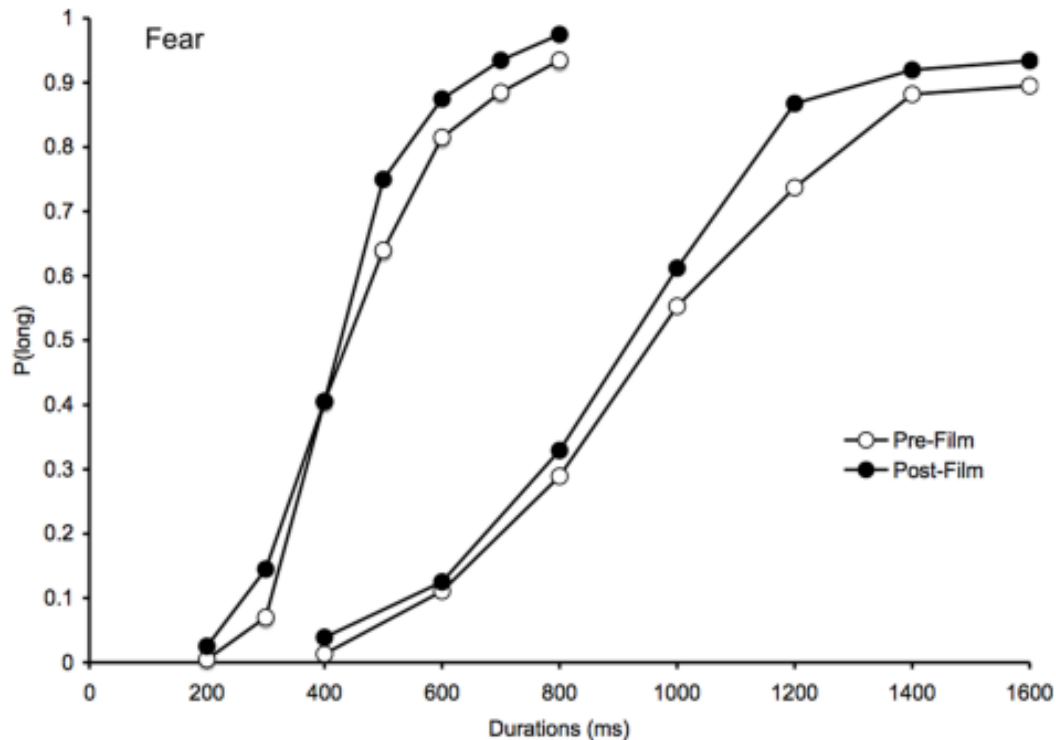


Figure 3. Arousal and time perception. Proportion of long responses plotted against probe durations (ms) for the bisection task before and after viewing the frightening films in the 200/400 and the 800/1600-ms duration range, (Gil & Droit-Volet, 2012).

A similar pattern has been observed with positive high-arousal emotions, such as excitement. While fear tends to produce negative high arousal, excitement can lead to a similar overestimation of time, despite the positive valence. This effect was shown in a study by Angrilli et al. (1997), where participants' emotional arousal and time estimates were manipulated using both positive and negative stimuli. The researchers found that high-arousal conditions, regardless of emotional valence, resulted in longer time estimates (Angrilli et al., 1997).

Mella et al. (2011) demonstrated that participants' time estimates were more accurate during states of moderate arousal but became increasingly distorted as arousal either heightened or decreased. Participants in low-arousal conditions, such as when bored or relaxed, tended to underestimate the length of time intervals, perceiving them as passing more quickly than they actually were (Mella et al., 2011).

Another factor closely related to emotional states and arousal is body temperature, which has been shown to affect the internal clock mechanism. Wittmann et al. (2010) explored the effects

of core body temperature on time perception and found that an increase in body temperature correlates with an acceleration of the internal clock, leading to longer perceived time intervals. This relationship between body temperature and time perception has important implications for understanding how arousal—which often raises body temperature—affects time estimation. Emotional arousal typically results in an elevated heart rate, increased respiration, and heightened sympathetic nervous system activity, all of which are linked to increases in core body temperature. Thus, emotional states that induce physiological arousal, such as anxiety, fear, or excitement, can lead to both time dilation and physiological changes that directly affect the perception of time. Wearden and Penton-Voak (1995) further expanded on these findings, demonstrating that time estimates in high-temperature environments tend to be longer, potentially due to the arousal-induced acceleration of the internal pacemaker.

In addition to temperature, heart rate variability (HRV) and other physiological measures of arousal have been linked to distortions in time perception. Van Wassenhove et al. (2008) found that fluctuations in heart rate correspond to changes in perceived time duration, with high-arousal conditions, characterized by increased heart rate, leading to a longer subjective experience of time. This further reinforces the idea that physiological arousal, whether driven by emotions or physical changes such as temperature, can modulate how time is perceived.

The implications of these findings are far-reaching, particularly in contexts where emotional states are heightened, such as during stressful situations, competitive sports, or high-stakes decision-making. Tse et al. (2004) examined how time perception is altered during moments of high arousal in sports and found that athletes under high pressure or in situations that demand rapid decision-making experience significant time dilation. This slowing down of time perception may, in fact, enhance performance, as it allows for more time to process information and react to fast-paced stimuli.

Similarly, Mella et al. (2011) found that participants' time estimates were more accurate during states of moderate arousal but became less accurate as arousal levels increased.

These findings have important implications for understanding the role of emotions in time perception, particularly in contexts where emotional states are heightened, such as during stressful situations, competitive sports, or high-stakes decision-making (Mella et al., 2011).

1.4 The role of cognitive and motor task in time perception

The relationship between cognitive load and time perception has been one of the major focus of research, as cognitive tasks often alter the subjective experience of time. Cognitive load can be understood as the mental effort required to perform a task, which can vary depending on the complexity and the nature of the task. Studies have consistently shown that high cognitive load can distort time perception, typically leading to the overestimation or underestimation of durations (Brown & West, 1990; Burnside, 1971; Gu et al., 2015; E. A. C. Thomas & Weaver, 1975; Zakay et al., 1983).

For example, Brown (1997) observed that various tasks—such as visual search, pursuit rotor tracking, and mental arithmetic—tend to cause underestimation of duration, with this effect becoming more pronounced as the difficulty of the task increases. Conversely, tasks involving temporal production specifically impair performance in mental arithmetic (Brown, 1997). This phenomenon has been extensively studied using various cognitive tasks, such as working memory tests, problem-solving activities, and decision-making tasks.

Similarly, research by Coull et al. (2004) demonstrated that the manipulation of cognitive load through dual-task paradigms leads to significant distortions in time estimation, with more demanding tasks resulting in greater discrepancies (Coull et al., 2004). In both studies, the durations used were very short, reaching up to 1200 milliseconds.

Moreover, the nature of the cognitive task itself plays a crucial role. Tasks that require sustained attention and vigilance, such as monitoring tasks, have been found to induce time dilation, where time is perceived as passing more slowly. On the other hand, tasks that involve high levels of cognitive engagement and rapid decision-making tend to result in time compression. A study by Polti and colleagues (2018) explores the impact of working memory load and attention on time perception. Participants were asked to estimate time intervals ranging from 30 to 90 seconds, representing relatively long durations for temporal estimation tasks, either focusing solely on the timing task (single-task condition) or while engaging in concurrent cognitive tasks of increasing difficulty (dual-task condition). Results showed that time durations were overestimated in the single-task condition compared to the dual-task condition, where there was a significant underestimation of time that correlated with the WM load across all

three intervals. Additionally, within the dual-task condition, the degree of underestimation increased with duration, meaning longer intervals were more greatly underestimated than shorter ones (**Figure 4**, (Polti et al., 2018)).

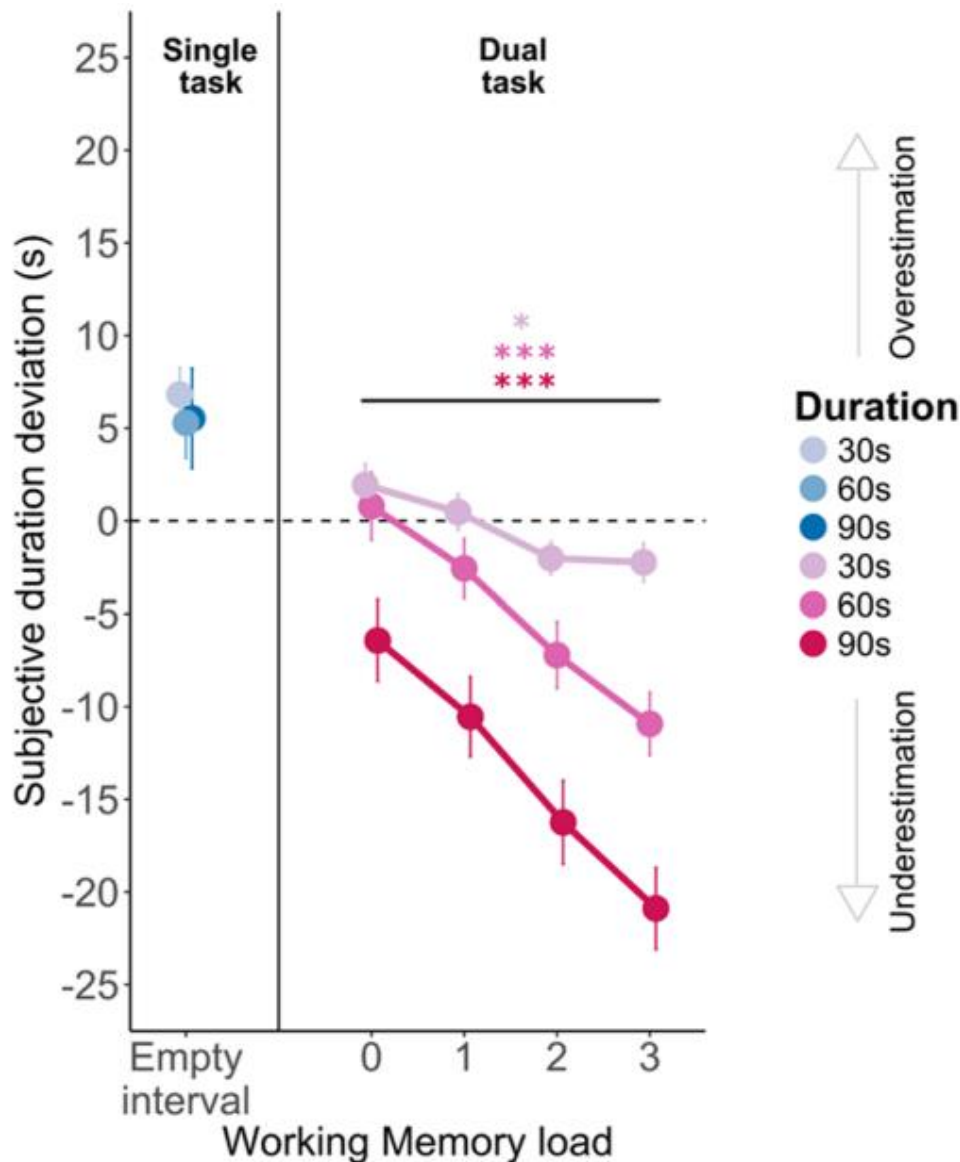


Figure 4. Working memory load and time estimation. Subjective duration estimates were transformed to express the amount of over/under-estimation in the single-task (blue) and in the dual-task (pink) as a function of WM load conditions. Hues are durations with lighter (darker) hues marking shorter (longer) durations. The dashed line represents the ideal observer so that positive values indicate a subjective overestimation of duration, and negative values indicate a subjective underestimation of duration (Polti et al., 2018).

When discussing cognitive load and cognitive tasks, it is crucial to distinguish between task difficulty and task complexity in order to understand how individuals interact with and perform

various cognitive tasks. Though the two terms are often used interchangeably, they refer to different aspects of a task's demands. Task difficulty is subjective and relates to how challenging an individual finds a task, often varying based on personal abilities, prior knowledge, and external conditions. On the other hand, task complexity is an objective characteristic of the task itself, defined by its structure, the number of elements involved, and the interdependencies between them.

Task difficulty is influenced by factors such as cognitive load, time pressure, and the amount of mental effort required. For example, Sweller's (1988) research into cognitive load during problem-solving tasks demonstrated that as the number of elements one must hold in working memory increases, so does the task's difficulty (Sweller, 1988). This subjective nature of difficulty means that the same task can be easy for one person but hard for another. Take basic arithmetic: a task of adding two single-digit numbers might be simple for an adult but difficult for a child who is still developing arithmetic skills. Similarly, studies such as those by Deary et al. (2010) show that individuals with faster reaction times tend to perform better on difficult tasks, indicating that difficulty varies based on the cognitive abilities of the participant (Deary et al., 2001).

External conditions also play a significant role in influencing how difficult a task feels. Tasks that are time-constrained are often perceived as more difficult because they increase the pressure to perform quickly, adding to the cognitive load. For instance, Braarud (2001) found that subjective workload and time pressure were major contributors to the perception of task difficulty, even when the structure of the task itself remained unchanged. This suggests that difficulty is not solely determined by the task's features but by the context in which it is performed (Braarud, 2010).

In contrast, task complexity refers to the inherent structure and demands of the task, independent of who is performing it. Complexity relates to the number of components in the task, how those components interact, and the degree of information processing required and the nature of the neural networks involved (P. Liu & Li, 2012). A task is considered complex when it involves multiple steps, requires the integration of various elements, or demands

coordination across different processes. For example, a visual search task where a participant must find a target among a large number of distractors is more complex than one with fewer distractors, as the cognitive system must process and filter more information (P. Liu & Li, 2012). The authors offer a detailed framework for understanding task complexity, breaking it down into structural, dynamic, and interactive dimensions. Structural complexity involves the sheer number of elements and the simultaneous information presented. For example, a task with numerous interacting components, such as a management simulation game requiring decision-making across multiple domains, would be high in complexity. Dynamic complexity occurs when a task evolves over time, requiring ongoing monitoring and adaptation, while interactive complexity refers to tasks that involve coordinating multiple processes simultaneously.

Studies have consistently demonstrated the distinction between task complexity and difficulty. For instance, Evangelisti et al. (1986) showed that problem-solving tasks became more complex as they required participants to manage more elements, even if they did not necessarily become more difficult for those with experience in the task (Evangelisti et al., 1986). Similarly, Campbell (1988) found that decision-making tasks involving numerous interdependent factors were more complex, requiring higher cognitive resources for planning and integrating information, whereas increasing time pressure heightened the difficulty of the same task by amplifying cognitive load (Campbell, 1988).

Neuroscientific studies offer further support for this distinction, showing that task difficulty and task complexity engage different but overlapping neural circuits. Task difficulty typically activates brain regions involved in cognitive control, attention, and working memory, such as the dorsolateral prefrontal cortex (DLPFC) and the anterior cingulate cortex (ACC). These regions help individuals regulate the effort needed to perform difficult tasks. Task complexity, in contrast, recruits brain areas involved in higher-order problem-solving and decision-making, like the posterior parietal cortex (PPC) and the ventromedial prefrontal cortex (vmPFC), reflecting the cognitive demand for integrating multiple components and processing interrelated information (P. Liu & Li, 2012).

Overall, the distinction between task difficulty and complexity is essential for understanding how different cognitive tasks are processed. Difficulty pertains to the subjective effort required to complete a task, while complexity refers to the objective structure of the task itself. This distinction has significant implications for cognitive research, as it helps clarify how people approach tasks of varying demands and how their performance may change under different conditions. Task complexity requires more intricate information processing and decision-making, while task difficulty increases the cognitive load based on the individual's experience, skills, and external constraints such as time pressure. This differentiation provides a richer understanding of how both complexity and difficulty shape performance in everyday and experimental contexts (Bedny et al., 2012; P. Liu & Li, 2012).

Motor activity is another factor that influences time perception. The execution of motor actions requires precise timing and coordination, which are closely linked to the brain's temporal processing systems. Research in this area has explored how different types of motor activity, ranging from simple repetitive movements to complex coordinated actions, affect the perception of time. Studies on sensorimotor synchronization, such as those by Repp and Su (2013), have shown that individuals can synchronize their movements with external rhythms, indicating a strong connection between motor control and time perception. This ability is essential in activities such as playing musical instruments, dancing, or engaging in sports, where precise timing is crucial (Repp & Su, 2013). Historically, activities as walking or maintaining balance were considered largely independent of cognitive demands (Bridenbaugh & Kressig, 2011; Clark et al., 1601; Paul et al., 2005). However, evidence has emerged indicating that these motor tasks involve complex cognitive and attentional processes. For instance, Ebersbach et al. (1995) demonstrated that while walking is generally a routine task, it becomes more cognitively demanding when combined with other tasks. Their study found that only the combination of mental and fine motor tasks interfered with balance regulation during walking, suggesting that the impact of a concurrent task on motor performance is contingent on the difficulty of the secondary task (Ebersbach et al., 1995). This finding is supported by subsequent research, which shows that gross motor tasks like walking and balance control can indeed affect cognitive functions, such as performing mathematical operations (Chong et al., 2010).

Despite these insights, much of the research has focused on simple motor tasks performed at normal speeds and rhythms. The investigation into how varying the difficulty of motor tasks affects cognitive performance has produced mixed results. For example, Kelly et al. (2010) found no significant impact of walking difficulty on performance in an auditory Stroop task, suggesting that walking difficulty might not always disrupt cognitive processing (Kelly et al., 2010). Conversely, Lindenberger et al. (2000) observed that participants performing memory encoding while walking on paths of varying complexity experienced greater cognitive interference with increased walking difficulty (Lindenberger et al., 2000). This discrepancy highlights the need for further exploration into how different levels of motor task difficulty influence cognitive performance, particularly when considering the complexity and nature of both the motor and cognitive tasks involved.

Overall, these studies underscore that gross motor functions, far from being purely automatic, engage significant cognitive resources, and their interaction with cognitive tasks is complex and context dependent. Indeed, combining cognitive-motor tasks, such as driving, playing a musical instrument, or performing in sports, require the integration of temporal information across both cognitive and motor domains. These tasks often involve multitasking, where individuals must manage cognitive demands while maintaining precise motor coordination. Further studies have explored how the complexity of the motor task interacts with cognitive load to influence time perception. For example, Yon et al. (2017) examined the effects of hand movements on the perception of short durations (ranging from 2 to 5 sec) for auditory stimuli and found that such movements can lead to temporal distortions (Yon et al., 2017). Similarly, studies by Yokosaka et al. (2015) and Tomassini and Morrone (2016) extended these findings to visual stimuli, demonstrating that the motor system plays a significant role in how time is perceived during fine movements when considering short durations (**Figure 5**, (Tomassini & Morrone, 2016; Yokosaka et al., 2015)). These investigations underscore that the coordination of fine motor tasks with sensory inputs can impact temporal judgments, often resulting in distortions linked to the motor system's activity. Additionally, the temporal integration of cognitive and motor processes is crucial for successful performance in many real-world scenarios.

The ability to accurately perceive and estimate time is essential for activities that require precise timing, such as playing music, engaging in sports, or driving. However, the underlying neural mechanisms that enable this integration to remain poorly understood, and further research is needed to explore how the brain coordinates these processes.

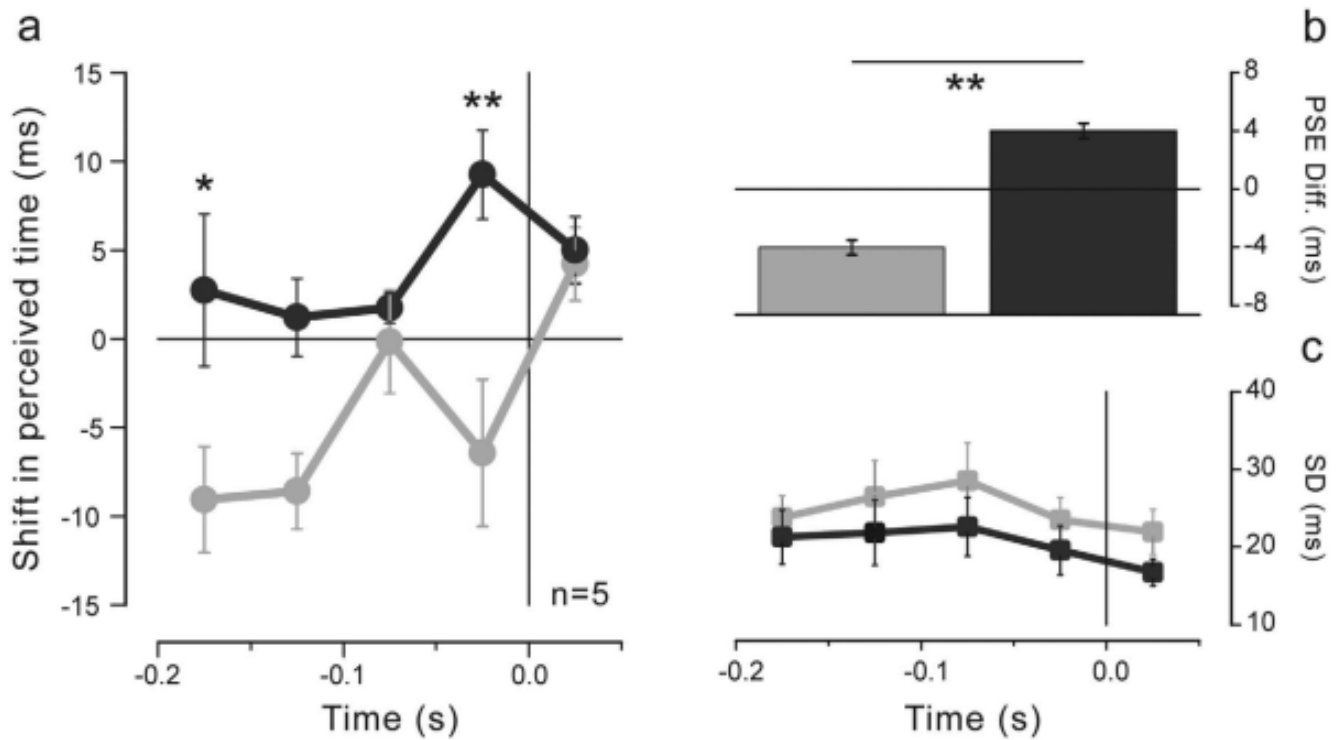


Figure 5. Perceived time and hand movements. (a) Perceived time as a function of stimulus presentation time with respect to movement onset time (zero time) averaged across subjects for the right (black) and left (gray) hand force direction in the isometric contraction condition. Results are expressed as the deviation of the PSEs from the mean individual PSE (i.e., the PSE averaged across stimulus latencies and movement directions, calculated separately for each subject). Negative and positive values indicate relative underestimation and overestimation of the time interval, respectively. Asterisks represent the significance level of one-tailed post-hoc *t*-tests. (b) Average deviation in the perceived temporal interval for the right (black) and left (gray) hand force directions. Asterisks represent the significance level of the paired-samples *t*-test. (c) Precision of the temporal judgments (SDs) as a function of stimulus presentation time with respect to movement onset time averaged across subjects for the right (black) and left (gray) hand force direction. Error bars represent standard errors of the means, (Tomassini & Morrone, 2016).

In contrast, fewer studies have addressed how gross body movements, such as walking, influence time estimation. For instance, two studies observed that while walking, participants overestimated the duration of time intervals, a phenomenon they attributed to the effect of movement on the internal clock. This overestimation may be due to the fact that physical activity, such as walking, can accelerate the internal clock's rate, thereby lengthening perceived intervals (Kroger-Costa et al., 2013; Sayali et al., 2018). Spapé et al. (2022) further supported these findings, suggesting that the increased pace of the internal clock during walking could contribute to the observed temporal distortions. They proposed that gross body movements like walking involve complex sensory-motor integration that affects how time is perceived (Spapé et al., 2022).

Overall, these studies highlight a growing interest in understanding how different types of motor activities influence time perception. While fine motor tasks have been shown to distort time perception in specific ways, gross motor activities such as walking appear to impact temporal estimation differently, often leading to overestimation. This emerging body of research suggests that both the nature of the motor task and the complexity of the movement involved are crucial factors in understanding how motor processes affect time perception. In addition, the influence of motor activity on time perception is further complicated by factors such as arousal and fatigue. For instance, during intense physical exertion, individuals may experience time as passing more slowly, a phenomenon linked to increased arousal and heightened sensory awareness. Conversely, in monotonous or repetitive motor tasks, time may appear to pass more quickly, possibly due to decreased cognitive engagement.

1.5 Objective of the thesis: examining cognitive and motor influences on time perception across task complexity and difficulty

In time perception literature, most studies focus on short durations, which don't fully reflect real-world experiences, where we engage in activities requiring more than a few seconds. To fill this gap, we designed a series of studies to explore time estimation under more ecologically valid conditions, expanding durations and introducing task combinations.

In the first study, we extended durations to over 2 minutes, examining how time perception might change when performing simultaneous motor and cognitive tasks. This setup allowed us to investigate interactions between these systems in temporal estimation, akin to the everyday experience of walking, where time can seem to move quickly or slowly depending on what we're thinking or doing. Observing significant interactions between cognitive and motor elements in this initial study led us to further disentangle these influences.

In the second study, we retained similar duration ranges but focused specifically on isolating the motor system by using walking tasks with varying difficulty levels. This design allowed us to examine the influence of motor demands on time perception. In existing literature, the relationship between time perception and motor activity has been primarily studied through fine motor movements, such as fine hand movements (Tomassini & Morrone, 2016). In contrast, we thoroughly investigated a common, everyday movement—walking—to provide a more ecologically relevant understanding of how motor activity shapes temporal experience.

Finally, in the third study, we isolated cognitive demands and introduced a novel approach by removing fixed time limits. Participants estimated the actual time taken for task completion, enabling us to separate the effects of estimated time from actual time spent. This allowed us to explore how task difficulty impacts time perception directly and how the intrinsic complexity of a task uniquely shapes temporal experience. Unlike previous paradigms, where we set predefined time intervals that included multiple trials, in this approach, the time participants estimate genuinely reflects the actual time spent on each single trial, accurately capturing moments when their attention is fully allocated to the task at hand.

This research contributes to existing literature by examining time perception across cognitive and motor domains in scenarios that resemble real-world experiences, deepening our understanding of how these demands shape our temporal experience in everyday contexts.

Chapter 2

Influence of Motor and Cognitive Tasks on Time Estimation

2. Influence of Motor and Cognitive Tasks on Time Estimation

2.1 Introduction

As broadly discussed in the introduction, time can be defined as a continuous sequence of events that occur from the past through the present to the future. It is not something we can see, touch or taste, but we can measure its passage in seconds, minutes, hours, days and so on, thanks to clocks and calendars. Time perception refers to a person's subjective experience of the passage of time (Sucala et al., 2010). The way in which we code temporal information has been under debate for a long time and is still little understood.

The most recognized theoretical model of time perception is the scalar timing theory (Allman et al., 2014; Buhsu & Meck, 2005; Gibbon, 1977; John H Wearden, 2003). This model posits that temporal judgments are constructed through a three-stage process: the pacemaker generates regular pulses, a switch controls the transmission of these pulses, and an accumulator counts them. The accumulator's content, representing elapsed time, is then compared with memories of previously stored durations. This model emphasizes the role of attention in temporal estimation, suggesting that attentional resources significantly impact our perception of time (Brown & West, 1990; Zakay & Block, 1996).

Besides time theories, experimental studies measuring time estimation make it clear that the perceived duration of events differs significantly from person to person and that each person's time perception is affected by multiple internal and contextual factors.

Widely studied physical factors that influence subjective time perception are body temperature and physiological arousal (J. H. Wearden & Penton-Voak, 1995). For example, studies have reported that increasing body temperature leads to an underestimation of time (Hoagland, 1933; van Maanen et al., 2019). Additionally, increasing arousal lengthens the perceived duration of events, whereas its decrease shortens duration estimation (Schwarz et al., 2012). Other studies have demonstrated that influencing factors are stress and anxiety (J. Liu & Li, 2019; Lueck, 2007; van Hedger et al., 2017), sleep (Soshi et al., 2010), drugs intake (Shahabifar & Movahedinia, 2016) and biological variables, such as age (Wittmann & Lehnhoff, 2005) and gender (Hanson & Buckworth, 2014).

Furthermore, some levels of experience in particular fields, which involved time counting, such as musical or sport expertise, could influence time estimation accuracy across different groups of individuals. For example, musicians show very low biases for duration reproduction compared to individuals with no musical training.

A critical contextual calibration is the central tendency effect, which leads to overestimating short intervals and to underestimating long ones (Gu & Meck, 2011; Jazayeri & Shadlen, 2010). Central tendency effects can be explained by the Bayesian computations in the estimation of magnitudes, for which duration judgments are derived not only from current sensory inputs but are also influenced by the acquired statistics of the distribution of previously experienced durations (Jazayeri & Shadlen, 2010; Mamassian et al., 2002; Shi & Burr, 2016). Contextual factors affecting time perception also include familiarity and numerosity of perceived stimuli (R. A. Block et al., 2010). For example, the less familiar the stimuli occurring within an interval, the longer they are perceived to be, because they require more storage space. Additionally, perceived durations lengthen as the number of elements contained in the intervals increases (Schiffman, 1977).

Temporal estimation is notably affected by concurrent non-temporal tasks, which can compromise accuracy. Studies suggest that the focus of attention plays a crucial role in duration judgments; concentrating solely on time typically results in overestimation, whereas dividing attention towards other cognitive tasks leads to underestimation (R. A. Block et al., 2010; Brown, 1985; Polti et al., 2018). There is a consistent body of evidence showing that cognitive and motor tasks mutually interfere (for a review, see (Al-Yahya et al., 2011)). For example, maintaining standing balance control while concurrently performing math subtractions has a damaging effect on cognitive performance and decreases speed and accuracy of responses (Chong et al., 2010). Furthermore, it has been found that counting backward aloud during walking leads to an impairment in the gait maintenance task (Beauchet et al., 2005).

Additionally, previous research has demonstrated that varying levels of cognitive load can alter subjective time perception, emphasizing the need to understand these dynamics across different contexts and conditions (Polti et al., 2018; Taatgen & van Rijn, 2011). A large body of studies conducted in the field of human time perception are restricted to estimations of brief

time intervals, order of 10–100 ms or order of seconds, while a few explored temporal estimations of intervals in the range of minutes (for reviews, see (Ivry & Schlerf, 2008; Wittmann, 2009)).

In the present study, for the first time, we measure prospective estimation of long time intervals (from 13 s to 132 s) while observers walk, to broaden time perception knowledge and fill some of the gaps in literature. Participants performed four different cognitive tasks of increasing difficulty (look, read, solve simple or hard mathematical operations) in two different motor conditions (walking on a treadmill or sitting on a chair). They were then asked to verbally report how much time had passed from the start to the end of the task. Although the best method to test interval timing in humans is still debatable (Buhusi & Meck, 2005; Oberfeld et al., 2014; Zakay, 1993), verbal estimation is the most ecological way to test the passing of time. Additionally, we purposely chose a verbal estimation task, instead of more common production/reproduction motor tasks, to avoid possible interferences with the motor condition. By combining cognitive and motor tasks, we can gain valuable insights into how these different systems interact and influence time perception, as previously discussed in the introduction. Understanding the interplay between these elements not only enhances our comprehension of temporal estimation but also sheds light on the cognitive processes involved when individuals engage in simultaneous tasks. This multifaceted approach may help bridge existing gaps in the literature regarding the effects of cognitive load and motor demands on time perception across varying contexts.

2.2 Materials and Methods

2.2.1 Participants

Sixteen young adults (eight males and eight females; mean age = 25.4 ± 0.7 years) participated in the experiment. All participants were naive as to the purpose of the study and had given written informed consent prior to participation. They were also required to possess a valid medical certificate for the physical activity involved. Before the experiment, all participants had to fill out a questionnaire regarding personal data, expertise in some specific fields (e.g., sport or music), sleeping habits, sleep–wake cycle, presence of optical defects, history of brain

damage, heart or respiratory disease, motor diseases, neurological problems, medication intake (e.g., psychotropic drugs or sleeping pills), psychological disorders (e.g., anxiety, depression), physical injuries, dyscalculia or any relevant pathologies. All selected participants had a normal or corrected-to-normal vision, no history of physiological or specific learning disorders and were not on any type of medication. All of them reported to have regular sleep–wake cycle and 7.5 h average night sleep duration (SE = 0.15). None of our participants is a professional athlete or musician. Additionally, before starting each session, we asked participants to rate their mental and physical tiredness with a 7-point Likert scale, obtaining an average value of 1.6 (SE = 0.06). Finally, participants were required to rate their math ability and math anxiety with a 7-point Likert scale. All of them reported having good ability in performing mathematical operations (mean score = 5.2, SE = 0.3), and none of them reported high math anxiety (mean score = 2.2, SE = 0.3). Participants were suggested to wear light sporting clothes and comfortable shoes during the walking sessions and to show up well rested (average night sleep = 7.3 ± 0.07 h before the experimental sessions), not having used exciting substances (e.g., alcohol) the night before the experiment.

The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the local ethics committee (“Commissione per l’Etica della Ricerca”, University of Florence, 7 July 2020, n. 111).

2.2.2 Apparatus and Set-Up

Stimuli were programmed and displayed on an iMac Retina 5K 27-inch (mid 2015, 3.3 GHz Intel Core i5 processor, MacOS Mojave software 10.12.6 (Cupertino, California), frame rate 60 Hz, 5120×2880 pixel resolution). In the sitting condition, observers sat in front of the display (60×33.5 cm), subtending $60^\circ \times 33.5^\circ$ of visual angle at a viewing distance of 57 cm (Figure 1a—left panel).

In the walking condition, observers were positioned on a JK Fitness treadmill (Supercompact 48 model, 48×130 cm walking belt), 80 cm away from the display, subtending $43^\circ \times 24^\circ$ of visual angle (**Figure 6a—right panel**). Given the different viewing distances in the two motor conditions, all stimuli sizes were adjusted to subtend the same degrees of visual angle in both conditions.

In both conditions, the experimental procedure was carried out in a temperature-controlled room (25° during the whole experiment). Participants' responses were entered on a computer keyboard by the experimenter. The experimenter measured the participants' head temperature through a non-contact infrared thermometer (Berrcom, JXB-178 model). Stimulus presentation and data collection programs were developed using the Psychophysics Toolbox extensions [64–66] for Matlab (R2020b version; Natick, Massachusetts: The MathWorks Inc.).

2.2.3 Procedure and Tasks

The whole experiment required four morning sessions (two for each motor condition) of about 2 h each, on different days. Conditions order was randomized across observers (7 participants performed the walking sessions first). Each participant took part in 200 trials for both motor conditions.

For each condition, time estimation of five different time intervals during four different tasks (look, read, solve simple, solve hard) was tested in all participants (**Figure 6**).

Time intervals were centered on 15, 30, 60, 90 and 120 s to allow comparisons of average estimates with previous studies that used this gross duration discretization [49]. However, the actual duration of each trial varied randomly in a 10% range of its central value but always taking an integer value of seconds. For example, the 15 s nominal time interval could take actual values of 13, 14, 15, 16, 17 s. This allows less predictability in time estimation and favors continuous and non-discretized observer responses.

Each possible combination of time interval and task was tested ten times per condition (**Figure 6b**). The trials were divided in blocks of ten, each containing every time interval twice, so that blocks had about the same duration (~12 min). Such short duration prevents participants from becoming tired. The tasks were randomly distributed across such blocks (see, for example, **Figure 6c**).

In the walking condition, the treadmill speed was not constant to prevent the participants from counting based on pace. In each block, a preset sequence of speeds, ranging from 1.4 km/h to 3 km/h, with changes ranging from 0.4 to 1.6 km/h every 20–40 s, was used for all observers. Before starting the experiment, observers were allowed to familiarize themselves with speeds and their changes used in the experiment.

To avoid physical and/or mental stress, in both conditions participants were allowed to take short breaks (of about 5 min) between blocks and a longer break (20 min maximum) to rest in the middle of the session (between the fifth and the sixth block). At the beginning and the end of each block, the experimenter measured participants' body temperature and asked them to rate their physical fatigue and mental tiredness on a 7-point Likert scale. The experimenter also checked the room temperature every 30 min and ensured that it remained stable throughout the whole session.

a



b

Cognitive task

<i>Motor condition</i>	<i>Time interval</i>	Look	Read	Solve simple	Solve hard
Walking/ Sitting	15s ± 2s	10	10	10	10
	30s ± 3s	10	10	10	10
	60s ± 6s	10	10	10	10
	90s ± 9s	10	10	10	10
	120s ± 12s	10	10	10	10

c

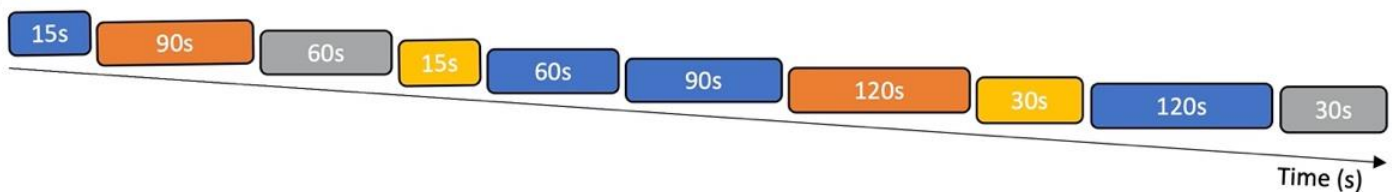


Figure 6. Experimental design. (a) Experimental set-up in sitting (**left panel**) and walking condition (**right panel**). (b) Number of trials per condition, time interval and cognitive task. Observers performed 10 trials for all possible combinations of time intervals and cognitive tasks in each motor condition. (c) Trial randomization in a block. Example of a block of 10 trials. Grey: look task; blue: read task; yellow: solve simple task; orange: solve hard task.

At the beginning of each trial, written instructions about the task to be performed were presented on a gray background (**Figure 7**). As soon as the participant reported being ready to start, the trial started with the appearance of a green circle ($2 \times 2^\circ$) in the center of the screen (800 ms), which told the observer to start estimating the passing of time. Then, the task began (specifics of each task are described in the paragraph below). At the end of the trial (whose duration was obviously unknown to the observer), a red circle ($2 \times 2^\circ$) appeared in the center (800 ms), informing the observers to stop temporal estimation. Then, a “time ruler” appeared on the screen, showing three scales of seconds from 0 to 60, one for each minute, along with the question “How much time has passed?” (**Figure 7a**). Observers were required to estimate how much time had passed between the start and stop signals, and their response appeared under the question, as the experimenter typed it in the computer. This graphic representation of time was used to make observers more inclined to give precise and diversified responses in terms of seconds, avoiding gross discretization of answers (such as “10 s”, “ $\frac{1}{2}$ min”, “1 min”, etc.).

Between the start and stop signal, observers were instructed to perform one of the following tasks requiring different amounts of cognitive load:

“*Look*” task: participants were instructed to look at a fixation point ($0.2 \times 0.2^\circ$) and pay attention to the passing of time. This task did not require any cognitive effort of the observers, who could potentially count the seconds (**Figure 7b**).

“*Read*” task: participants were required to read aloud some math operations written on the screen and pay attention to the passing of time. Stimuli were black-arial font numbers ($5 \times 3^\circ$) presented on a gray background for 4 s. The first operation was presented after a random period of time from the start signal (500 ms–2 s), and all were alternated with a blank screen of random duration (from 1 to 4 s), to avoid time counting based on the number of stimuli presented. This task was introduced as “attention control”, since reading activity might interfere with

time counting, while requiring a minimum cognitive load and sustaining observers' attention to the cognitive task (**Figure 7c**).

“*Solve simple*” task: participants were required to solve simple sums of a 1-digit number plus a 2-digit number (without carry over, e.g., $24 + 5$) and pay attention to the passing of time. The result of the operations was never higher than 100. The first operation was presented after a random period from the start signal (500 ms–2 s). Operations ($5 \times 3^\circ$) were presented on a gray background until the observer reported aloud the solution or for a maximum of 6 s if no solution was provided. As soon as the observer reported the solution, the experimenter pressed a key to record the response time. The solution was then displayed on the screen while the experimenter typed it in the computer. Then, a blank screen was presented for 1 s before the next operation. This task requires a modest amount of processing load and cognitive effort, which make counting time explicitly very unlikely (**Figure 7d**).

“*Solve hard*” task: participants were required to solve hard sums of 2-digit numbers (e.g., $37 + 48$) and pay attention to the passing of time. Numbers to be summed were never greater than 50. The procedure was the same as for the *solve simple* task. This task requires concentration and high cognitive effort, which prevents time counting.

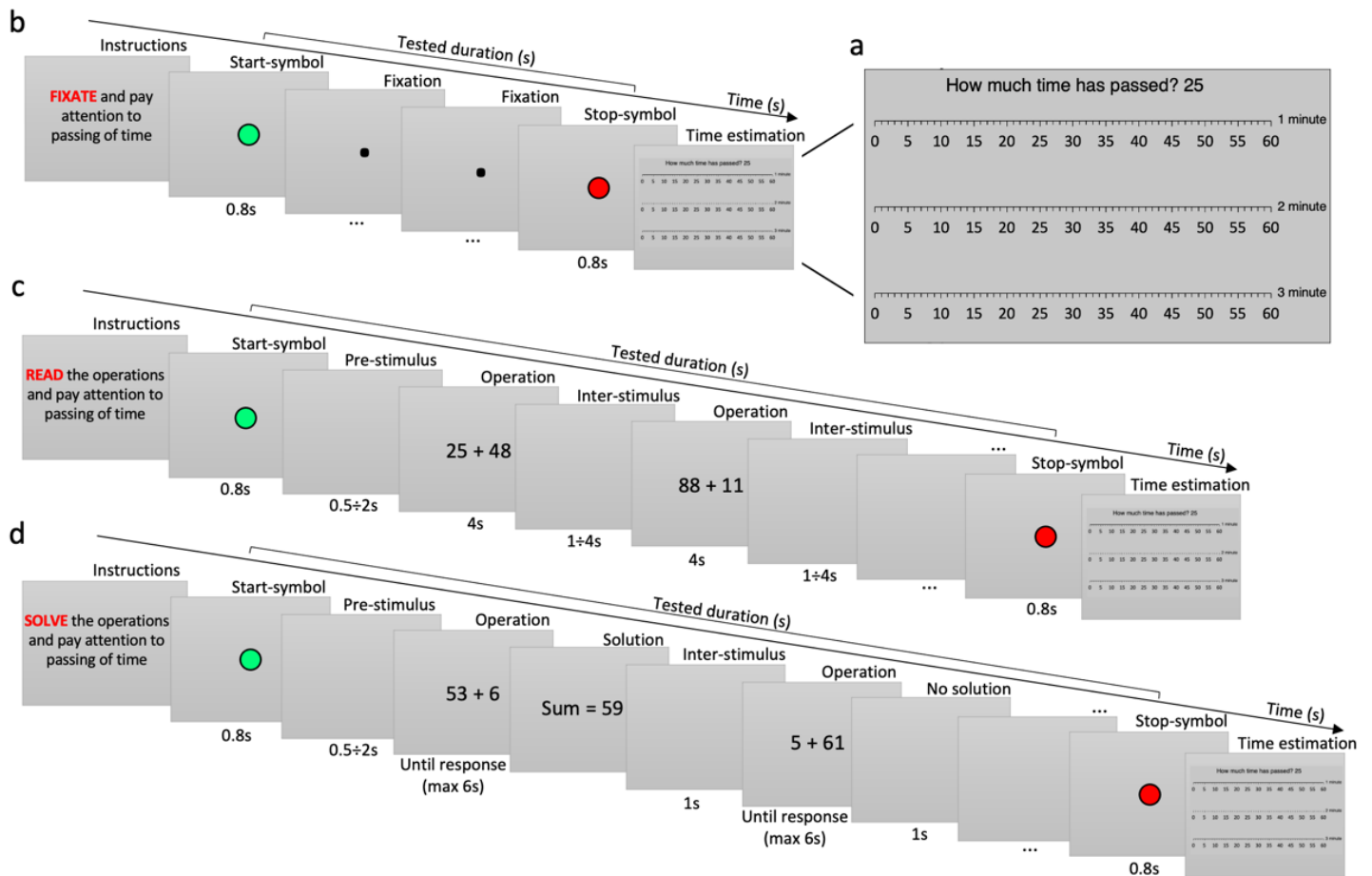


Figure 7. Procedure and tasks. (a) Time ruler. Ruler shown at the end of each trial to allow participants to express how much time had passed while they were performing the task. In the example shown, the participant estimated 25 s. (b) Look task. (c) Read task. (d) Solve task. Example of solve simple task. The solve hard task follows the same procedure but consists of harder mathematical sums. Red words report the task to be performed in the trial. The green circle informs the observers to start estimating the passing of time; the red circle informs the observers to stop estimating the passing of time.

2.2.4 Data Processing and Statistical Analysis

For each trial, we recorded both the true time, and the time estimated by the participant. From these values, the time difference in seconds between time effective and estimated durations (estimation bias) was determined. For solve tasks, we also measured the percentage of correct responses and the average response time.

To check the normality of data distributions, Shapiro–Wilks tests were performed for each task and time interval. Since most of those tests revealed deviations from normality, non-parametric statistical tests were used where needed, and an outlier-removal procedure was applied when estimating variances from data to get rid of the longer tails.

To filter the outliers, we first determined a pseudomedian estimate of each distribution by evaluating the Hodges–Lehman statistics; then, we dropped all data deviating by more than 3 SD above or below this pseudomedian [67]. All averages and variances used in our analysis were then calculated on this filtered sample. When a variance of our variance estimate was needed, we estimated it by a bootstrap procedure of the whole process (including the filtering stage), in order to achieve the best accuracy and robustness in spite of the presence of the non-gaussian tails.

To measure with the least squares fitting methods how estimation biases or their uncertainties change with duration, data were averaged over smaller time intervals (2–3 sec) to avoid artificially inflating the variance of data with the effect of the drift of the average estimate within the five larger bins mentioned above.

Below, we reported a detailed list of tests performed to measure different effects.

To assess the effect of all factors playing a role in our study, we performed a linear mixed-effects model with estimation as outcome variable, and cognitive task (look, read, solve simple, solve hard), time interval (15 s, 30 s, 60 s, 90 s and 120 s) and motor condition (walking or sitting) as fixed effects. We also included the variable subjects as random effects and the variable sex as covariate. The p -values obtained from post hoc analyses were adjusted using the Bonferroni correction.

For detailing the effect of the cognitive task, we also tested whether some estimation biases (averaged over participants in the same task and the same time interval) were not significantly different from zero with one-sample Wilcoxon signed-rank tests.

Then, to investigate how temporal estimation changes as a function of duration, for each condition, data of all participants for all tasks and durations, binned over 2 s, were fitted with a linear function with 2 parameters. χ^2 were used as goodness-of-fit tests. Z-tests were used to assess whether the fitting curves' slopes were significantly different from zero and to compare the slopes for each task and condition.

For measuring the dependency of estimation uncertainty on duration, RMSE values, binned over 2 s durations, were fitted with 1-parameter linear functions, and χ^2 were used as goodness-of-fit tests. To statistically compare the trend of RMSE in each task and condition, the slopes and intercepts of the fitting curves were compared with z-tests.

Then, to evaluate whether our data follow the scalar timing theory, RMSE values were fitted as a function of estimated time with 1-parameter linear functions, and χ^2 were used as goodness-of-fit tests. The coefficients of variation for each task and condition were compared with the z-tests.

The averaged percentages of correct responses and response times for the solve simple and solve hard tasks in the two motor conditions were compared with two-way ANOVA analysis, with factor condition (two levels: sitting vs. walking) and time interval (five levels: 15 s, 30 s, 60 s, 90 s, 120 s). To account for potential individual differences in cognitive performance, we correlated estimation bias with task performance and reaction times to determine if individual abilities influenced temporal estimation.

Finally, to exclude the possibility that results could depend on physical fatigue, mental tiredness and temperature, all factors that are known to affect time estimation, we tested the correlations of these parameters with the block number with regression model fits. R-squared were used as goodness-of-fit tests. T-statistics assessed the significant increase/decrease in these variables as a function of block number (by testing whether the angular coefficient of the fitting curve was different from zero). The same analyses were carried out to exclude the effect of block number on time estimation itself. Particularly, we checked that percentage time estimation difference in the look and solve hard tasks (averaged across all time intervals) did not change as a function of block number. Matlab (R2020b version) and Excel (16 version) software were used for data processing and graph creation. Data fitting was performed with Mathematica software (Wolfram). R (4.0.3 version) and JASP (Version 0.8.6) software were used for statistical analyses.

2.3 Results

Mixed-effects linear model analysis revealed the main effect of cognitive task ($\chi^2(3) = 2265.5$, $p < 0.001$), time interval ($\chi^2(4) = 991.6$, $p < 0.001$), motor condition ($\chi^2(1) = 41.0$, $p < 0.001$) and their interaction ($\chi^2(12) = 21.3$, $p < 0.05$), on time estimation. No significant differences were found as a function of sex ($\chi^2(1) = 2.07$, $p > 0.05$). In the next paragraphs, we will investigate in detail the effects of these three main factors.

2.3.1 Effects of Cognitive Task on Time Estimation

Raw data of all participants for the different types of tasks in the sitting and the walking condition are reported in **Figure 8a** and **8b**, respectively. For the large majority of time intervals, data are not normally distributed. Regardless of the motor condition, data clearly show that participants tend to overestimate time if they are not required to perform any particular task (look task, see **Figure 8a,b—first panel**). They report a more or less accurate estimation while they are reading (read task, see **Figure 8a,b—second panel**). They mostly underestimate durations if they are engaging in demanding tasks, with increasing underestimation for harder tasks (solve simple and solve hard tasks, see **Figure 8a,b—third and fourth panels**). Estimations averaged across all participants for each time interval are reported in Table 1.

Table 1. Time estimation averaged over every participant for each task and time interval (with standard errors across participants), in the sitting and walking conditions.

Sitting	15 s	30 s	60 s	90 s	120 s
Look	M = 21.8, SE = 1.5	M = 35.6, SE = 1.7	M = 66.3, SE = 2.8	M = 97.3, SE = 3.2	M = 122.9, SE = 3.4
Read	M = 18.1, SE = 1.2	M = 31.8, SE = 1.7	M = 58.5, SE = 2.4	M = 87.3, SE = 1.7	M = 110.3, SE = 3.4
Solve simple	M = 14.4, SE = 0.7	M = 27.1, SE = 1.1	M = 51.5, SE = 1.7	M = 73.6, SE = 2.8	M = 94.7, SE = 4.3
Solve hard	M = 12.7, SE = 0.7	M = 23.1, SE = 1.1	M = 45.2, SE = 2.2	M = 65.9, SE = 2.9	M = 86.7, SE = 3.9
Walking	15 s	30 s	60 s	90 s	120 s
Look	M = 24.4, SE = 1.8	M = 38.7, SE = 2.4	M = 71.2, SE = 3.8	M = 100.6, SE = 4.5	M = 124, SE = 4.7
Read	M = 19.4, SE = 1.5	M = 31.8, SE = 1.9	M = 58.2, SE = 3.9	M = 87.8, SE = 4.5	M = 110.8, SE = 5.4

Solve simple	M = 13.6, SE = 1.1	M = 23.7, SE = 1.3	M = 45.1, SE = 2.5	M = 66.2, SE = 4.1	M = 83.7, SE = 4.7
Solve hard	M = 10.9, SE = 0.8	M = 20.8, SE = 1.4	M = 38.6, SE = 2.6	M = 55.9, SE = 3.1	M = 71.9, SE = 4.6

Differences between effective and estimated durations (estimation bias), averaged across participants, for each task and time interval, are reported in Figure 6c,d for the sitting and walking conditions, respectively.

Temporal estimation in some combinations of task and time interval is very accurate. In fact, in some cases, the estimation bias is not significantly different from zero. Overall, participants give the most accurate estimation while reading, even if not for all the tested time intervals. During other tasks, estimation accuracy greatly changes based on the duration. For this reason, in the next section we will describe the effects of duration on the estimation bias in each task (represented by the fitting curves in Figure 4c,d, see Section 2.4 for details).

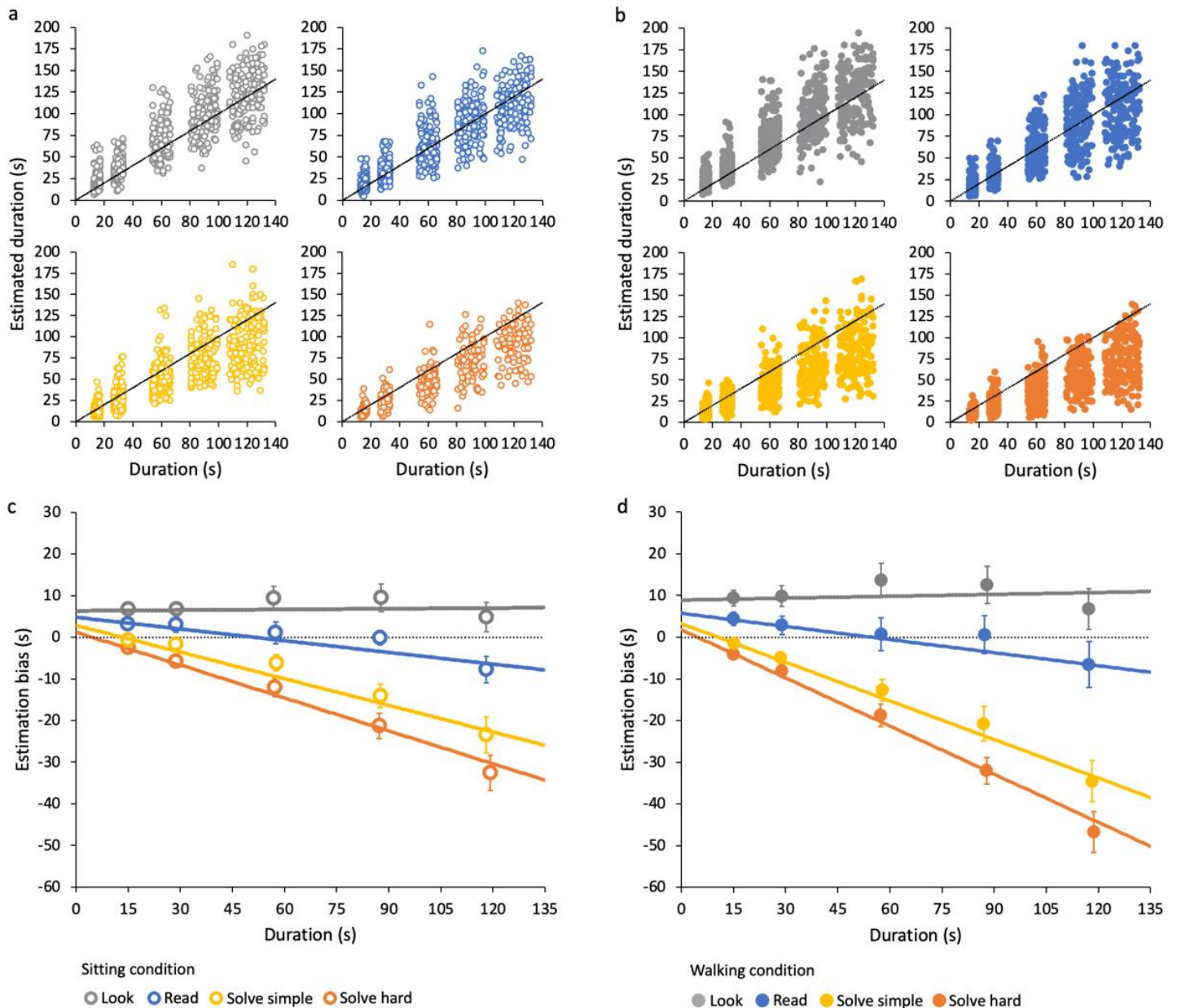


Figure 8. Time estimations during different tasks. (a) Sitting condition: different panels represent all data in different tasks (see different colors in the legend). (b) Walking condition: different panels represent all data in different tasks (see different colors in the legend). (c) Sitting condition: estimation bias averaged over time intervals and participants. The dashed lines represent best fits calculated on data averaged on smaller time intervals (2 s, see text). Look: intercept = 6.4 ± 0.9 , slope = 0.005 ± 0.2 , $\chi^2(35) = 45.9$. Read: intercept = 4.8 ± 0.8 , slope = -0.09 ± 0.2 , $\chi^2(35) = 50.1$. Solve simple: intercept = 2.8 ± 0.6 , slope = -0.2 ± 0.2 , $\chi^2(35) = 57.8$. Solve hard: intercept = 1.2 ± 0.4 , slope = -0.3 ± 0.01 , $\chi^2(35) = 36.1$ (d) Walking condition: estimation bias averaged over time intervals and participants. Solid lines represent best-fit curves, calculated as in c). Look: intercept = 8.9 ± 0.8 , slope = 0.01 ± 0.2 , $\chi^2(35) = 35.6$. Read: intercept = 5.7 ± 0.8 , slope = -0.1 ± 0.2 , $\chi^2(35) = 41.6$. Solve simple: intercept

$= 3.3 \pm 0.6$, $slope = -0.3 \pm 0.2$, $\chi^2(35) = 40$. *Solve hard*: $intercept = 1.8 \pm 0.4$, $slope = -0.4 \pm 0.01$, $\chi^2(35) = 36.7$. *Error bars are SE across participants.*

2.3.2 Effects of Duration on Time Estimation

Results show that estimation bias depends on duration in a different way for each cognitive task. Since data are not normally distributed within the time intervals considered, they were averaged over 2 s time intervals for linear fitting purposes (see Section 2.4). For clarity, however, fitting curves are shown together with data averaged over the unbinned time intervals in Figure 8a,b for the sitting and walking condition, respectively. Fit parameters and goodness-of-fit values are reported in the figure caption.

In the look task, the estimation bias does not vary with time, both in the sitting and walking conditions; that is, slopes are not statistically different from 0 (sitting: $z = 0.3$, $p > 0.05$; walking: $z = 0.8$, $p > 0.5$). In the read task, in both motor conditions, the estimation bias becomes slightly more negative (increases in absolute value), going from shorter to longer durations; that is, slopes are both statistically different from 0 (sitting: $z = -5.3$, $p < 0.001$; walking: $z = -5$, $p < 0.001$). In the two solve tasks, the fitting curves have steep negative slopes, all significantly different from zero (solve simple sitting $z = -11.5$, $p < 0.001$; solve simple walking $z = -16.7$, $p < 0.001$; solve hard sitting $z = -19.5$, $p < 0.001$; solve hard walking $z = -27.1$, $p < 0.001$). The slopes of look, read and solve tasks are significantly different from each other. Additionally, the slopes for solve hard task are more negative than those for solve simple, indicating that time underestimation while performing cognitive-demanding tasks increases with task difficulty. Note that estimation biases (Figure 8c,d) have the same trends in both motor conditions, although they differ in magnitude, as will be described in the next section. To shed some light on the mechanisms underlying time estimation, we measured uncertainties for different durations in all tasks and motor conditions. **Figure 9** shows root mean square errors (RMSE) calculated over 2 s bins for linear fitting purposes (see Section 2.4). In each task and condition, we found RMSE to increase with duration. In the sitting condition, the variabilities associated with different tasks are comparable (see caption of Figure 9). In the walking condition, the variabilities associated with low-demanding look and read tasks are

higher than those for high-demanding solve tasks (see caption of Figure 9). Comparisons of fitting curves in the walking and sitting condition are described in the next section.

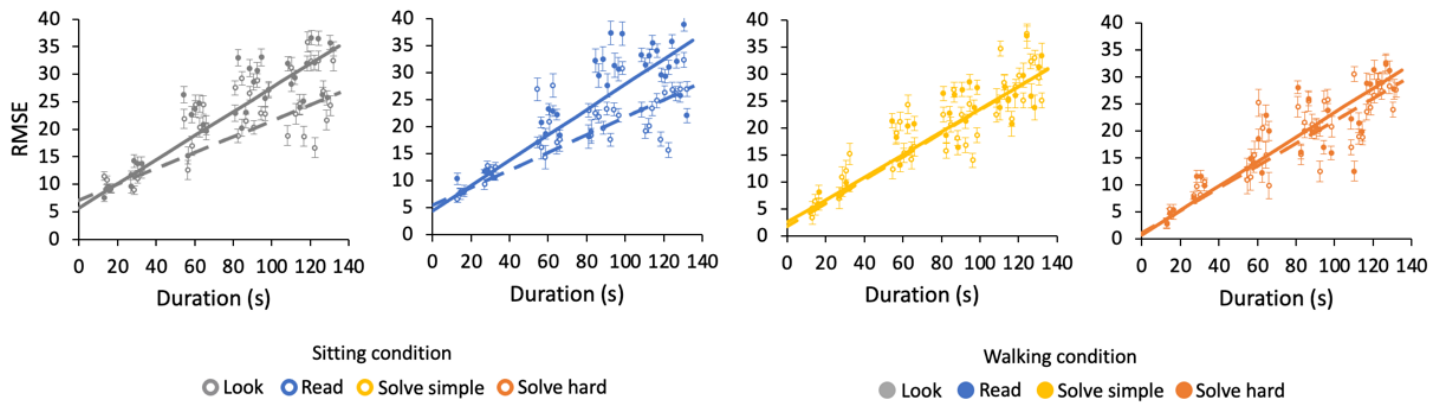


Figure 9. Estimation uncertainty as a function of duration. Averaged RMSE computed on 2 s intervals for all tasks and conditions with their best-fit curves. Different panels correspond to different tasks (see colors in the legend). Sitting condition: open symbols—dashed lines; walking condition: solid symbols—solid lines. Sitting condition—Look: slope = 0.14 ± 0.02 , intercept = $4.6 + 0.2$; Read: slope = 0.16 ± 0.01 , intercept = $4.1 + 0.4$; Solve simple: slope = 0.22 ± 0.02 , intercept = $1.7 + 0.1$; Solve hard: slope = 0.21 ± 0.01 , intercept = $0.8 + 0.1$. Walking condition—Look: slope = 0.22 ± 0.1 , intercept = $4.9 + 0.1$; Read: slope = 0.23 ± 0.01 , intercept = $3.2 + 0.2$; Solve simple: slope = 0.21 ± 0.01 , intercept = $1.2 + 0.1$; Solve hard: slope = 0.23 ± 0.02 , intercept = $0.9 + 0.2$.

We also fitted RMSE as a function of estimated time (not shown here). Coefficients of variation (CV) for each task and condition (slopes of fitted data) are reported in **Figure 10**. Results show that CV in the sitting condition are statistically the same for all tasks. Instead, in the walking condition, CV for solve simple and solve hard tasks are higher than those for look ($z = -3.0, p < 0.01$; $z = -2.0, p < 0.05$, respectively) and read tasks ($z = -2.7, p < 0.01$; $z = -2.7, p < 0.01$, respectively).

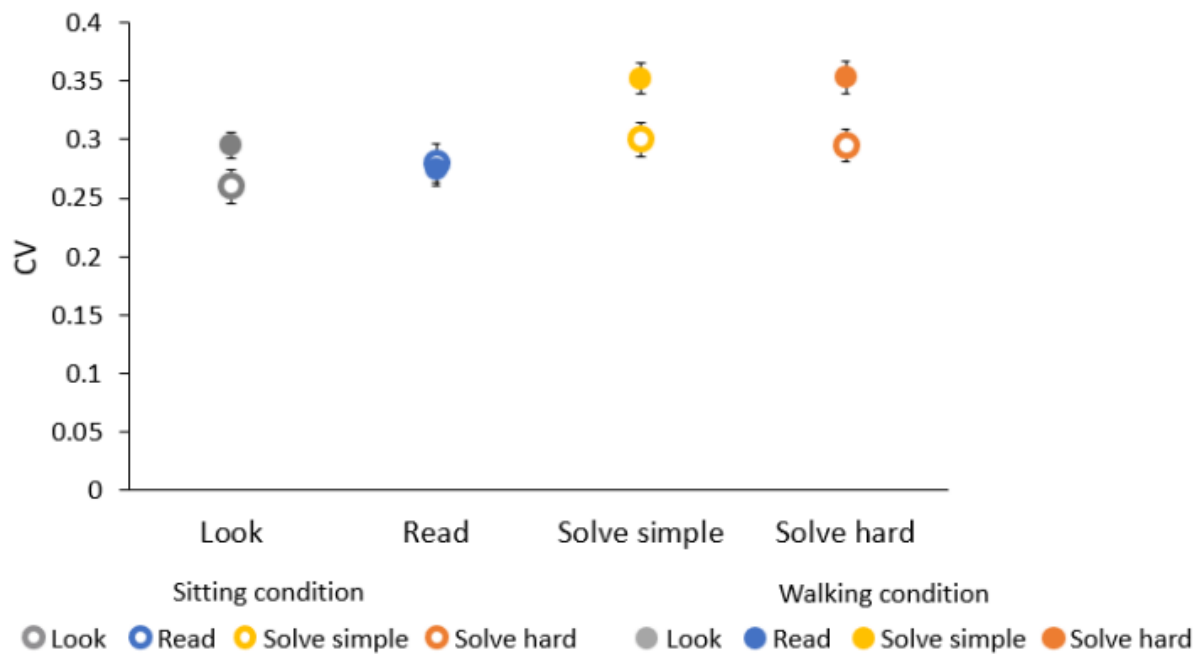


Figure 10. Coefficient of variation for different tasks in sitting and walking conditions. Data shown and their errors are the results of best linear fitting of binned RMSE as a function of estimated time.

2.3.3 Effects of Walking on Time Estimation

Another interesting result emerging from our data is the difference in time estimation between the walking and the sitting conditions.

To analyze the overall effect of walking on time estimation accuracy during different tasks, we compared the slopes (**Figure 11a**) and the intercepts (**Figure 11b**) of the data fitting curves in the two motor conditions. In the two solve tasks, the slopes are higher in the walking than in the sitting condition (solve simple: $z = 2.5$, $p < 0.05$; solve hard: $z = 4$, $p < 0.001$). This means that during walking, a larger time underestimation is observed, particularly during demanding tasks. The intercepts, representing a constant error in estimation, are also larger in the walking than in the sitting condition in all tasks, although not to a statistically significant level.

Estimation biases averaged across participants for each task and time interval in the two motor conditions are reported in **Figure 11c** to highlight the effects of walking at each time interval. Results show that estimation during walking is less accurate within each cognitive task, but the direction of the error differs across them. Participants' overestimation for the look task tends to be larger during walking compared to sitting for all time intervals, although it is not

statistically significant. For the read task, the accuracy is comparable between the two conditions in all time intervals. In the solve tasks, walking induces a larger underestimation at all time intervals, significant for the longer durations.

Estimation during walking is also less precise than when sitting, only for low-demanding tasks (see Figure 9). Indeed, RMSE in the walking condition are higher than in the sitting condition in the look ($z = -2.3, p < 0.05$) and read tasks ($z = -2.7, p < 0.05$).

Coefficients of variation for solve tasks in the walking condition are also larger than in the sitting condition (solve simple, $z = 2.0, p < 0.05$; solve hard, $z = 2.0, p < 0.05$) (see Figure 10). The size of the increase is about 15%. There is no difference between CV of the walking and sitting condition for read and look tasks.

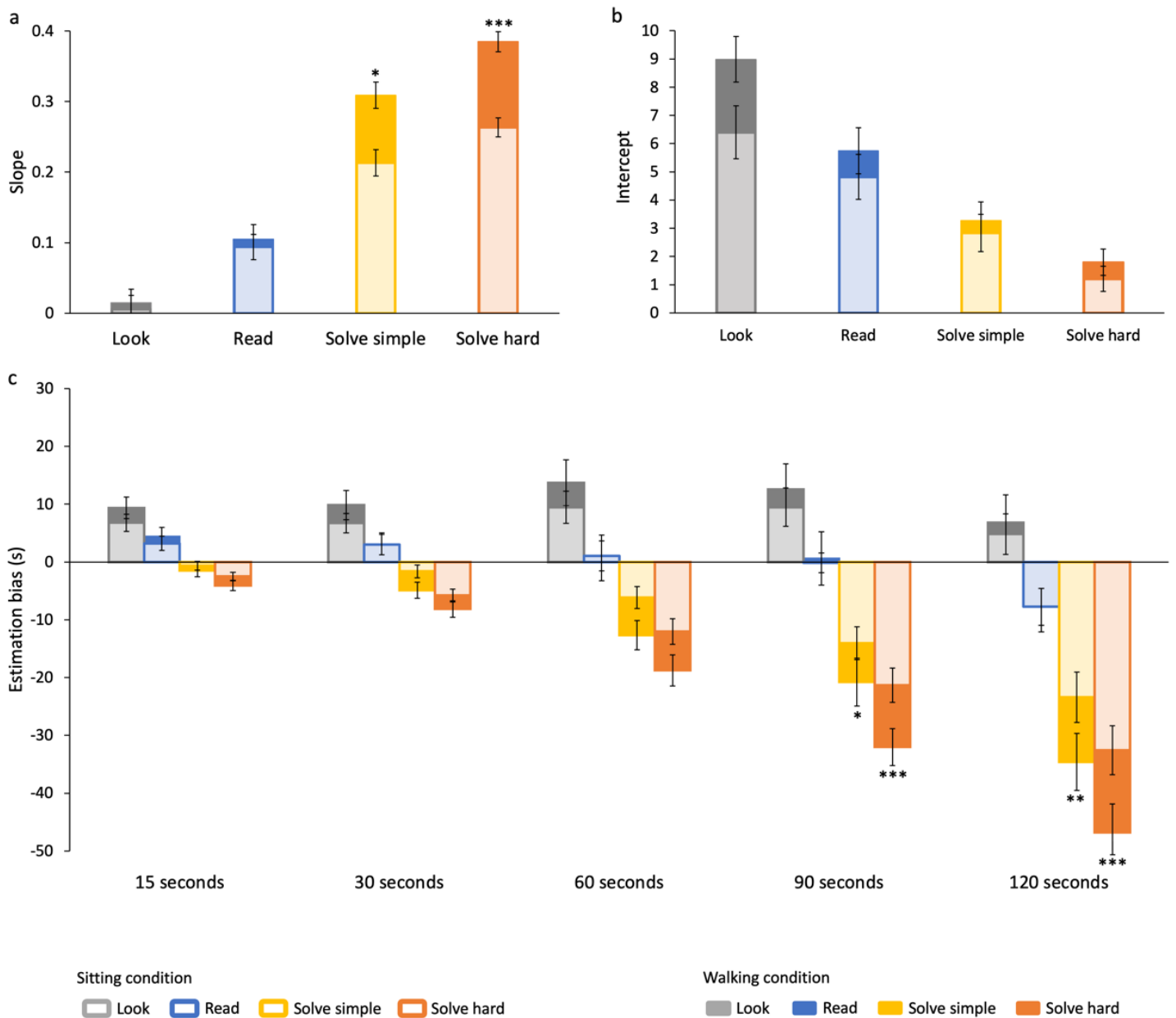


Figure 11. Comparison of time estimation during walking and while sitting for all tasks. (a) Slopes of best-fit lines, shown in Figure 8c,d. Asterisks mark statistically significant differences with z-tests: * $p < 0.05$, *** $p < 0.001$. **(b)** Y-axis intercepts of best-fit lines, shown in Figure 8c,d. **(c)** Estimation bias averaged over time intervals and participants. Asterisks mark statistically significant pairwise post hoc comparisons: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

To compare the magnitude of the effects induced by the cognitive and motor processing on time estimation, percentual biases (e.g., relative to time interval) were considered. To evaluate the effect of the motor condition per se in our data, differences between estimates in the walking and sitting condition in the look task, not requiring cognitive efforts, have to be considered. An average effect of about 7.5% is found (cf. dark-gray vs. light-gray bars in Figure 11), with

a maximum effect of about 17% at 15 s. To evaluate the effect of cognitive tasks per se, differences between estimates in the solve and look tasks in the sitting condition, not requiring motor processing, have to be considered. The average effect is about 37% (average difference at all time intervals of light-yellow and light-orange bars vs. averages of light-gray bars in Figure 11). The maximum influence of cognitive tasks is about 62%, corresponding to the difference between solve hard and look task at 15 s time interval (cf. light-gray vs. light-orange bars in Figure 11).

2.3.4 Effects of Walking on Cognitive Performance

Additional results emerge from the comparison of participants' performance in those tasks requiring the solving of mathematical operations of different difficulties (solve simple and solve hard tasks), in the sitting and walking condition.

First, the percentages of correct solutions for mathematical operations differ across the two tasks and conditions but not across time intervals (see **Figure 12a**). Indeed, as expected, participants gave a higher number of correct answers to easier operations than to harder ones, in both motor conditions. Averaged across all durations, in the sitting condition, the averaged percentage of correct responses is $99.6 \pm 0.2\%$ for simple sums and $94.7 \pm 1.1\%$ for hard sums, while in the walking condition, it is $99.6 \pm 0.1\%$ for simple sums, and 91.3 ± 1.2 for hard sums. Only in the solve hard task does the main effect of motor condition emerge ($F(1,15) = 11.9$, $p < 0.01$, $\eta^2 = 0.1$). Thus, the percentage of correct responses to simple operations is the same in the two conditions, possibly due to ceiling effects. Instead, the performance for hard operations is significantly lower in the walking than in the sitting condition for all time intervals, with an average decrease of 4%.

Differences between the two tasks and the two conditions also emerge when considering the averaged time needed by participants to solve the operations (see **Figure 12b**). Again, as expected, in both conditions, participants solve the easier operations faster than the harder ones. In the sitting condition, the averaged response time is 1.45 ± 0.05 s for simple sums and 3.02 ± 0.1 s for hard sums, while in the walking condition, it is 1.62 ± 0.04 s for simple sums and 3.16 ± 0.1 s for hard sums. For both tasks, there is the main effect of condition (solve simple:

$F(1,15) = 6.1, p < 0.05, \eta^2 = 0.2$; solve hard: $F(1,15) = 4.7, p < 0.05, \eta^2 = 0.03$) but not of time intervals and their interactions. Thus, the average time necessary to solve simple and hard sums is significantly lower in the sitting than in the walking condition. Interestingly, the average time differences between walking and sitting conditions for solve simple and solve hard, respectively, 0.17 and 0.14 s, are statistically comparable (paired-sample t-test: $t(15) = 0.35, p > 0.5$); that is, walking affects response times in the same way, independently of task difficulty. Overall, our results suggest that performing a motor task impairs the performance in a concurrent cognitive task and slows down response times. In addition to the primary analyses, we also examined the relationship between estimation bias and individual performance across tasks. Correlations between estimation bias and reaction times, as well as task performance, were all weak, indicating that individual differences did not substantially influence temporal estimation.

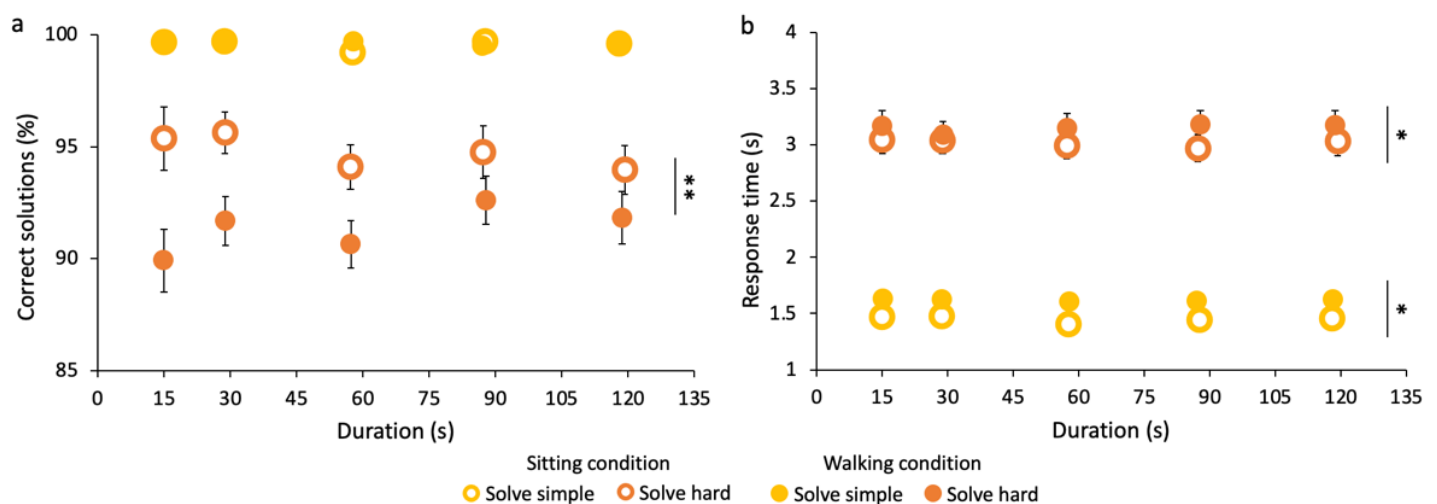


Figure 12. Performance in the math tasks while walking and sitting. (a) Percentage of correct solutions. (b) Response time to operations. Responses for correct and incorrect solutions are considered. Asterisks mark statistically significant differences with ANOVAs: * $p < 0.05$, ** $p < 0.01$. Error bars are SE across participants.

2.3.5 Controls of Influencing Variables: Physical Fatigue, Mental Tiredness and Body Temperature

Since participants were subjected to a long, demanding experiment, it was likely that, despite the frequent breaks, they became increasingly tired with the succession of blocks. To check for this, after each block, participants were asked to rate their physical fatigue with a 7-point

Likert scale. On average, for the sitting condition, the minimum score reported was 1.4 ± 0.1 , and the maximum was 1.7 ± 0.1 , with an increase of 0.3 from block 1 to 10 (averaged across the two sessions). For the walking condition, the minimum physical fatigue score was 1.7 ± 0.2 , and the maximum was 3.3 ± 0.3 , with an increase of 1.6 from block 1 to 10. Regression model fits were performed to investigate the relationship between physical fatigue and block number. As expected, in the sitting condition, physical fatigue does not increase with the block number ($b = 0.01$, $t(8) = 2.1$, $p > 0.05$). In the walking condition, however, the subject's fatigue significantly increases with blocks, that is, with the walking time ($b = 0.15$, $t(8) = 6.9$, $p < 0.001$).

Since the experiment included trials requiring participants to solve mathematical operations, the whole data collection was also highly cognitive demanding for the participants. For this reason, they were asked to rate their mental tiredness after each block. On average, for the sitting condition, the minimum score was 1.7 ± 0.1 , and the maximum was 2.9 ± 0.2 , with an increase of 1.2 from block 1 to 10 (averaged across the two sessions). For the walking condition, the minimum score was 1.9 ± 0.2 , and the maximum was 3.4 ± 0.2 , with an increase of 1.5 from block 1 to 10. Regression model fits showed that mental tiredness significantly increases with the succession of blocks, both for the sitting ($b = 0.13$, $t(8) = 6.9$, $p < 0.001$) and the walking condition ($b = 0.16$, $t(8) = 8.1$, $p < 0.001$).

Since physical and mental fatigue actually change from the beginning to the end of the experimental sessions, we performed further analyses to check that their increase did not influence time estimation across blocks. To do this, we evaluated time estimation differences in the look and solve hard tasks (the easiest and the most difficult tasks) from block 1 to 10, averaged across all participants, durations and the two sessions. Linear regression analysis shows that time estimation difference for both tasks and both conditions does not change as a function of block number (all t-statistics yield $p > 0.05$).

Furthermore, the experimenter measured participants' temperature at the beginning of each trial, to check it remained stable during the whole data collection. Averaged across the two sessions, the medium temperature of participants was 36.7 ± 0.01 °C in the sitting condition

and 36.5 ± 0.02 °C in the walking condition. Regression analysis confirms that body temperature does not increase during the experiment, neither in the sitting ($b = 0.002$, $t(8) = 0.9$, $p > 0.05$) nor in the walking condition ($b = 0.0003$, $t(8) = 0.06$, $p > 0.05$).

These analyses indicate that our results for the different cognitive tasks, time intervals and motor conditions must depend on cognitive and motor processes alone, which influence accuracy and precision of time estimation.

2.4 Discussion

In the present study, the ability of human participants to estimate time while concurrently performing cognitive and motor tasks was investigated for the first time. In each trial, participants were randomly required to perform a cognitive task of variable difficulty (look at the screen, read aloud some numbers, solve easy or hard mathematical sums) and estimate the duration elapsed from the beginning to the end of the trial. The effects of gross body movements on time estimation were investigated here by measuring verbal prospective estimation in two different motor conditions: sitting on a chair or walking on a treadmill. Here, we tested the prospective estimation of durations of up to two minutes (specifically from 13 to 132 s). While durations below a second have received a great deal of attention in the human timing literature, a lower number of studies tested the effects of cognitive tasks on such long intervals ((Polti et al., 2018), for review, see Refs. (R. A. Block et al., 2010; Grondin, 2010; Gu et al., 2015; Matthews & Meck, 2016)). However, in ecological situations, human activities require more than just a few seconds, and we usually do have to estimate time in terms of minutes and even more while performing other tasks. Additionally, by using such an extended time interval, we were able to measure how estimation accuracy changes across durations, allowing us to test quantitatively the time estimation mechanisms underlying different concurring mental tasks. First, when participants are not involved in any particular cognitive task, such as simply looking at a blank screen (“*look* task”), they tend to overestimate temporal intervals, in agreement with previous works (Burnside, 1971; Molet et al., 2011; Polti et al., 2018). Time overestimation could depend on the fact that paying attention only to time lengthens subjective durations (R. a. Block, 2003; R. A. Block et al., 2010; E. A. C. Thomas & Weaver, 1975; Zakay et al.,

1983). The bias as a function of durations remains constant, suggesting a fixed shift in time estimation. Polti et al., 2010 (see Ref. (Polti et al., 2018)), using the same paradigm and task, and similar long durations, found data consistent with our effect. In the *look* task, time overestimation tends to be higher in the walking condition, as in previous studies (Kroger-Costa et al., 2013; Sayali et al., 2018), although the effect is not statistically significant. Estimation bias as a function of duration is flat, as in the sitting condition. Estimation uncertainty is also lower in the walking condition, meaning that there is higher variability during walking.

When participants read numbers presented on the screen (“*read* task”), their accuracy is quite high, especially for intervals of intermediate duration. Indeed, subjective durations are compatible with the effective elapsed duration for 30 to 90 s time intervals. Estimation bias shows that there is a modest overestimation for the briefest durations, which decreases with time, becoming a modest underestimation for the longest durations. Overall, these results confirm that when participants are engaged in intermediately demanding cognitive tasks, such as reading, they are more accurate in time estimation compared to easier or more difficult tasks (Polti et al., 2018). These effects could also be accounted for by the allocation of attention. It might be that the reading activity is not demanding enough to fully deviate attention away from time (which would cause time underestimation), but, at the same time, it prevents subjects from only paying attention to time (which would cause time overestimation). This interpretation would also explain the small overestimation at 15 s and the small underestimation observed around 120 s, since participants might still be able to concentrate on a temporal task for a few seconds, but then, the succession of numbers to be read progressively diverts the subject’s attention from the temporal task. In this cognitive task, the effect of walking is less prominent than in all other tasks, being non-existent in the estimation accuracy and only emerging in estimation uncertainty (higher variability during walking).

Time estimation is completely different while participants are solving mathematical operations of low or high difficulty (“*solve* simple” and “*solve* hard” tasks). They tend to underestimate temporal durations with greater magnitude in the most difficult task. These effects are in line with the results usually found with prospective estimation paradigms, as the one used here, in which cognitive effort induces duration underestimation (Polti et al., 2018). There might be a potential influence of the number of math prompts on temporal estimates. In the ‘solve simple’

condition, participants can complete more sums within, for example, the 2-minute time frame compared to the ‘solve hard’ condition, leading to more total stimuli. However, if the number of stimuli were influencing time perception, we would expect greater underestimation of time in the ‘solve simple’ condition. Instead, we observe more underestimation in the ‘solve hard’ condition, indicating that it is the cognitive load that affects time perception, rather than the number of stimuli. Underestimation while participants are engaged in cognitive-demanding task might also be explained by the hypothesis that diverting attention away from time shortens subjective duration (R. A. Block et al., 2010; Brown, 1985, 1997; Schiffman, 1977; E. A. C. Thomas & Weaver, 1975). The estimation bias progressively increases as a function of duration, and the increase is more pronounced for the harder task. Furthermore, estimation uncertainty increases with duration in a way that is consistent with an underlying mechanism with fixed relative uncertainty on time estimation.

Very interestingly, when participants perform the math operations while walking, they underestimate temporal durations more than they already do while they are seated. Moreover, the increase in bias with increasing duration is more pronounced in the walking condition. Contrary to low-demanding tasks, there are no differences in variability between the two motor conditions. There are no existing hypotheses for explaining these results, given our novel experimental paradigm of concurrent motor and non-temporal cognitive-demanding tasks while performing time estimation. We can speculate that the higher time distortion might be due to the fact that the cognitive effort spent to perform the motor task adds to that needed to perform the cognitive one. The hypothesis that motor and cognitive processing interact is in line with the studies showing that the motor task induces an impairment on performance in the mental task (Al-Yahya et al., 2011; Chong et al., 2010). We tested this hypothesis and found interference in cognitive performance. While walking, participants provided a larger number of wrong solutions to the hard mathematical operations and needed more time to provide the answer to the easy and the hard operations compared to sitting. Thus, this cognitive–motor interaction could also be reflected in time estimation distortions. We aimed to create the most ecologically valid situations possible to make time perception as close to real-life experiences as possible. However, despite walking being a natural activity, the laboratory setting itself could have influenced the results in the cognitive-motor interaction.

The time estimation effects observed in this study do not depend on biological variables, such as body temperature or physical and mental fatigue. The latter slightly increased during each experimental session, as reported subjectively, but never reached levels high enough to cause physical and mental stress.

Overall, our results show that both cognitive and motor processes influence time estimation. However, it should be noted that the magnitude of their effect is very different, since the cognitive task has a much higher effect than the motor task (about four times as much) at all time intervals.

The representation of time in the brain is still under investigation, but there is general agreement on the fact that time perception processes do not rely on a specific brain structure but rather on a broad network of brain areas (Coull et al., 2004; Merchant et al., 2013). Particularly, studies indicate the role of basal ganglia, supplementary motor area, frontal lobes and the cerebellum, which are also in charge of cognitive and sensorimotor functions (e.g., walking) (Coull et al., 2004; Leisman et al., 2016). Moreover, the right parietal cortex, which is consistently implicated in mathematical cognition (Wu et al., 2009), has also been found to be crucial in time estimation (Hayashi et al., 2018). Therefore, we can speculate that the interference effects we found in our study reflect the neural interaction between cognitive, motor and time perception functions, which share some neural resources.

2.5 Conclusions

We conclude that time estimation is influenced by both cognitive and motor tasks. The effects found in our study could be framed within the widespread pacemaker accumulator model, which assumes the presence of an internal clock sending pulses to an accumulator to keep track of the elapsed time [2–4]. In this framework, attention acts as a switch that alters the number of pulses transferred to the accumulator and then to working memory (attentional allocation model, (Allman et al., 2014; Grondin, 2010; Matthews & Meck, 2016)). Our results—temporal overestimation while fully attending to time and temporal underestimation during cognitive-demanding tasks—are in line with this model. In fact, when attention is diverted from just the passage of time by a cognitive task, the switch is opened and leads to the loss of

a certain number of pulses, thus decreasing the perceived duration. In every task, the variability increases linearly with time estimates, in agreement with the broadly demonstrated scalar timing theory (Buhsu & Meck, 2005; Grondin, 2010; Matthews & Meck, 2014). It is also notable that our cognitive task, while causing an underestimation, does not increase the relative variability of the estimate, indicating that the amount of lost time is relatively constant from trial to trial.

The additional underestimation induced by simultaneous motor and cognitive tasks is harder to frame in the literature, since no previous studies combined motor, mental and temporal tasks in a single paradigm. It is also interesting that the same motor task by itself does not induce significant changes in time perception (except possibly for a slight extra bias), so the two effects do not simply add linearly. We can speculate that the motor task increases somehow the weight of the concurrent cognitive effort, leading to additional openings of the switch and, consequently, to a lower number of accumulated pulses than in the sitting condition. This reflects also in the relative uncertainty (coefficients of variation), which is higher in the walking than in the sitting condition. The additional cognitive effort could be provided by irregular walking speed used in our paradigm, which requires participants to continuously adapt to the random change of speed, making the deambulatory activity non-automatic (Paul et al., 2005). It would be interesting to test this hypothesis by using different paradigms, including regular constant walking speed or even more pronounced speed changes.

Chapter 3

Time estimation during different motor activities

3. Time estimation during different motor activities

3.1 Introduction

As discussed, a fundamental principle of this study is to align our research with everyday activities and the routines we engage in. Everyday situations require the ability to perform two or more tasks at the same time, such as walking and using mobile phones, driving and talking, cooking while listening to the news. A large body of evidence shows interactions between motor and cognitive domains. It has been demonstrated that simultaneously performing motor and cognitive tasks leads to the decline of one or both performances (for a review, see (Al-Yahya et al., 2011)). The most common paradigm for studying motor-cognitive interference is the concurrent performance of hand movements and verbal assignment (Hiscock et al., 1989; Matheson et al., 2014; Serrien, 2009; Simon & Sussman, 1987). For instance, hand movements affect verbal counting performance (Serrien, 2009), visual processing capacity (Künstler et al., 2018), object-naming (Koester & Schack, 2016; Matheson et al., 2014), speech tasks (Dromey & Benson, 2003), and working memory (Logan & Fischman, 2015; Spiegel et al., 2013).

Some studies also used other motor tasks such as maintaining balance or walking (for a review see (Bayot et al., 2018)). These gross motor functions have traditionally been considered automatic activities that do not require the involvement of cognitive processing in young healthy adults (Bridenbaugh & Kressig, 2011; Clark et al., 1601; Paul et al., 2005). However, this assumption has been challenged by some evidence highlighting that they are complex mechanisms requiring cognitive and attentional processes ((Ebersbach et al., 1995; Herold et al., 2018; Lajoie et al., 1993; Nieborowska et al., 2019; Pizzamiglio et al., 2017; Plummer et al., 2015; Woollacott & Shumway-Cook, 2002), for a review, see (Leone et al., 2017)). For example, Eberbash (1995) investigated the effect of different tasks (cognitive, fine motor, and combined tasks) on walking, finding that only combined mental and fine motor demands interfere with the regulation of balance during walking, suggesting that the effect of a concurrent task on gross body movements depended on the difficulty of the secondary task (Ebersbach et al., 1995). On the other end, walking and balance control reduce cognitive abilities, such as solving math operations (Castellotti et al., 2022; Chong et al., 2010).

However, most of these studies only used simple motor tasks, using people's normal speeds and rhythm. Only a few studies investigate the effect of motor task difficulty on cognitive tasks, finding controversial results. For example, Kelly and colleagues (2010) did not find any influence of walking difficulty on the performance in auditory stroop task (Kelly et al., 2010). On the contrary, Lindenberger (2000) required participants to perform memory encoding while walking through two tracks with different path complexity, finding that the higher the walking difficulty the stronger the interference with the cognitive performance (Lindenberger et al., 2000).

As already discussed in the introduction, in everyday life, one common cognitive activity that humans perform while walking is perceiving elapsed time. According to the scalar expectancy theory (Gibbon, 1977; John H Wearden, 2003), in addition to the initial clock process, there are two further levels: the memory and the decision-making stage ("Funct. Neural Mech. Interval Timing.," 2003). The timing errors are due either to a change in the pacemaker's rate or to attentional resource allocation to the timing task (*attention allocation model*, (Brown & West, 1990; Macar et al., 1994a; Zakay et al., 1983)). A wide range of research involving dual task paradigms demonstrated a shortening of perceived time with the increasing of the concurrent task difficulty (Brown, 1985; Castellotti et al., 2022; Rammsayer & Ulrich, 2005; Zakay & Tsal, 1989); indeed, as theorized by the *attention allocation model*, paying attention only to time induces temporal overestimation, whereas diverting attention away from time causes time underestimation, with a positive relationship with the difficulty level of the concurrent nontemporal tasks ((Burnside, 1971; Macar et al., 1994a; E. A. C. Thomas & Weaver, 1975), for reviews, see (R. A. Block et al., 2010; Gu et al., 2015)).

Only recently, some studies have investigated whether temporal perception can be affected by motor processes, mainly using fine movements. Indeed, many of them tested the effects of hand movements on judging short durations of auditory (Yon et al., 2017) and visual stimuli (Tomassini & Morrone, 2016; Yokosaka et al., 2015), finding that time distortions are linked to the motor system. So far, to our knowledge, only a few studies investigated how time estimation is affected by gross body movement like, finding overestimation of temporal

durations during walking and speculated that movement speeds up the internal clock (Kroger-Costa et al., 2013; Sayali et al., 2018).

In the first study, for the first time, we combined time estimation of long durations (up to two minutes), four different cognitive tasks of increasing difficulty, and two different motor conditions (Castellotti et al., 2022). Our results showed that, when participants were sitting on a chair (absence of motion), they tended to underestimate durations during cognitive-demanding tasks and overestimate durations while attending only to time (in line with the *attentional allocation model* (Allman et al., 2014; Grondin, 2010; Matthews & Meck, 2016)). Also, estimation uncertainty increased linearly with time estimates in all tasks, in agreement with the scalar timing theory (Buhusi & Meck, 2005; Grondin, 2010; Matthews & Meck, 2014). When participants were walking, estimation bias during mental tasks was more pronounced, as well as estimation uncertainty, whereas no clear motor-induced effects emerged without a concurrent cognitive task. Overall, it seemed that the motor load adds somehow to the cognitive load in distorting temporal judgment, but whether the motor tasks themselves interfere with time estimation remains unclear. We could hypothesize that a demanding walking activity might require a sufficient amount of attention to affect time estimation per se in the absence of another concurrent cognitive task. According to the *scalar timing theory*, this would mean that walking tasks might directly open the switch, causing a loss of pulses and thus decreasing the perceived duration, as well as other demanding cognitive tasks do. In the previous study, we did not observe this effect, maybe due to the relatively automatic walking task used in the experiment.

The exact nature of the interaction between walking activity and other cognitive tasks (e.g., linear or non-linear) and the relative amount of attention dedicated to the two processes still remain unclear. The observed smaller effect exerted by the motor *vs* cognitive task suggests a larger amount of attention dedicated to the latter. However, by using just one type of relatively automatic motor activity, we could not deduce the nature and the relative strength of the interaction (Castellotti et al., 2022).

For these reasons, building on findings of our previous work, this study aims to manipulate the difficulty of both cognitive, requiring solving mathematical operations of increasing difficulty, and motor tasks simultaneously, testing three different types of walking: forward regular-speed walking, forward irregular-speed walking, and backward irregular-speed walking. We then compare the effects of these three types of walking on time estimation, by measuring accuracy and uncertainty. If the walking activity directly affects time estimation, in the absence of another cognitive task, we expect larger time underestimations and larger uncertainties for backward irregular-speed walking than for forward regular-speed walking. By comparing the effects of different combinations of difficulty levels of the two tasks, it would be also possible to shed some light on the nature and strength of their interactions.

The findings of this work will highlight whether complex body movements can interfere with time estimation and clarify how different motor and cognitive processes interact during time estimation.

3.2 Materials and methods

3.2.1 Participants

15 young adults ($\mu=24.8$ years, $SE=0.8$) participated in the experiment. All the participants were university students, naïve to the purpose of the study and they had given written informed consent prior to participation. They were also required to possess a valid medical certificate for the physical activity involved. Before data collection, they were asked to fill out a questionnaire regarding personal data, expertise in some specific fields (e.g., sport or music), sleeping habits, presence of any optical damage or pathological disorders (e.g., dyscalculia), medication intake (e.g., psychotropic drugs or sleeping pills). They were also asked to subjectively rate their math-anxiety level and their ability in solving mathematical operations, on a 7-point Likert scale. All participants had normal or corrected-to-normal visual acuity, did not take any type of medication, did not present any brain damage, and were free of cognitive disorders. All reported having a regular sleep-wake cycle (average night sleep duration of 7.5 ± 0.3 hours). None of them was a professional athlete or musician and they reported, on average, having good ability in solving mathematical sums ($\mu=4.7$, $SE=0.4$) and low math

anxiety ($\mu=2.1$, $SE=0.3$) Participants were asked to wear light sporting clothes and comfortable shoes during the experimental session and to not assume stimulating substances the night before the experiment. Before each experimental session, they were asked to rate their stress level and their mental and physical tiredness, on a 7-point Likert scale.

The study was conducted according to the guidelines of the Declaration of Helsinki and approved by the local ethics committee (“*Commissione per l’Etica della Ricerca*”, University of Florence, 7 July 2020, n. 111”).

3.2.2 Setup

Participants walked on a JK Fitness treadmill (Supercompact 48 model, 48×130 cm walking belt), positioned 80 cm away from the display, that subtended $43^\circ \times 24^\circ$ of visual angle. Stimuli were programmed and displayed on an iMac Retina 5K 27-inch (mid 2015, 3.3 GHz Intel Core i5 processor, MacOS Mojave software 10.12.6 (Cupertino, California), frame rate 60 Hz, 5120×2880 pixels resolution). Participants’ responses were entered on a computer keyboard by the experimenter. The experimenter measured the participants’ head temperature through a non-contact infrared thermometer (Berrcom, JXB-178 model). Software for presentation of stimuli and data collection was developed using the Psychophysics Toolbox extensions for Matlab (R2018b version; Natick, Massachusetts: The MathWorks Inc.).

3.2.3 Procedure and conditions

The entire experiment required three sessions of 2 hours per participant on three different days, one for each motor condition: 1) forward regular-speed walking, 2) forward irregular-speed walking, 3) backward irregular-speed walking (**Figure 13A**). The first is an automated movement performed without any particular effort (Bridenbaugh & Kressig, 2011; Clark et al., 1601; Paul et al., 2005): each participant freely chose the most comfortable walking speed by adjusting it on the treadmill console before starting the session. The average speed chosen is $2.5 \pm 0.2(SE)$ km/h. The second requires some motor control and body balance since the speed changes unpredictably for the walker; indeed, the experimenter randomly changed it every 1-3 seconds, in the range from 2km/h to 8km/h (maximum speed to avoid running). The third is a very unusual movement for humans and can be considered highly demanding because it

requires attention to be implemented and continuous motor control to adapt to the random change of speed; indeed, during the session, we randomly varied the speed of the treadmill in the range from 1km/h to 5km/h. At the beginning of the backward irregular-speed walking condition, participants could get familiar with the required unusual body movement.

While walking, participants were asked to pay attention to the passing of time and perform three different cognitive tasks of increasing difficulty. Each trial started with the instructions explaining the task to be performed from the appearance of the *Start-symbol* ($2 \times 2^\circ$ green circle presented in the center of the screen for 800 ms) informing the participant to start estimating the passing of time, to the *End-symbol* (red circle) informing to stop temporal estimation. The least demanding task required to fixate at a small point ($0.2 \times 0.2^\circ$) presented on the screen center (**Figure 13B**). The task of medium difficulty consisted in solving easy mathematical sums of a 1-digit number plus a 2-digit number (e.g., $13+4$). The result of the operations was never higher than 100. The most difficult tasks consisted in solving hard mathematical sums of a 2-digit number plus a 2-digit number with carryover e.g., $38+49$, **Figure 13C**). In both solve tasks, math operations ($5 \times 3^\circ$) were presented on a gray background and participants had 6 seconds to give the solutions. The experimenter pressed a key to record the response time and entered the participants answer. Then, a blank screen was presented for 1 s before the next operation (Figure 10C). At the end of each trial, after the stop symbol, a “time ruler” appeared on the screen, showing three scales of seconds from 0 to 60, one for each minute, along with the question “How much time has passed?”. We use a verbal estimation paradigm, as it is the ecological way humans use to judge the passing of time and it does not interfere with body movements. Participants’ responses were typed by the experimenter on the keyboard. The time ruler has been used to promote a finer time response by participants.

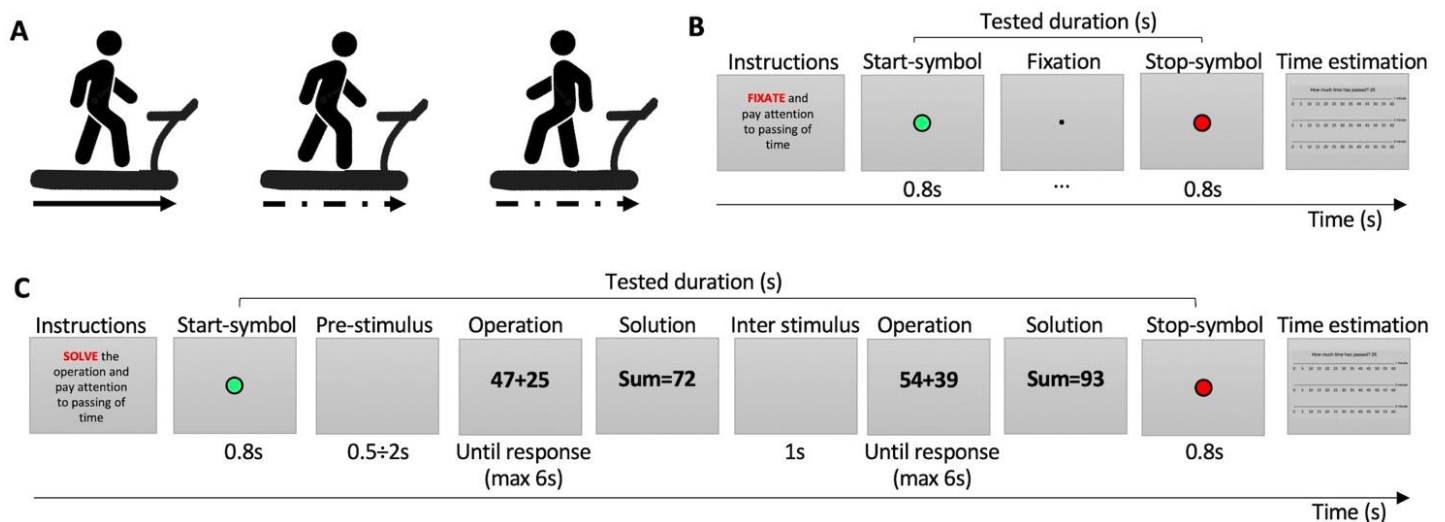


Figure 13. Procedure and tasks. (A) Motor conditions. From left to right: forward regular-speed walking, forward irregular-speed walking, backward irregular-speed walking. (B) Easy task. (C) Hard task. In the instructions, the red word indicates the cognitive task to be performed. The green circle indicates the beginning of time estimation; the red circle indicated the stop of time estimation.

Since human activities require more than just a few seconds and our interest was to test how humans estimate time in real-life situations, we test long temporal intervals. Specifically, we tested random durations along a continuum in the range of 15 s to 120 s; the two extreme values were always presented at least once in each task, whereas the other durations to be tested were randomly selected (with integer values of seconds).

Participants performed a total of 135 trials (15 for each cognitive task, for each motor condition). The order of the motor conditions was randomly assigned: as a result, five participants performed the forward regular-speed walking first, six performed the forward irregular-speed walking first, four the backward irregular-speed walking condition first. Each experimental session was divided into 9 blocks, interspersed with short breaks. At the beginning of each block, experimenters checked the participant's body temperature. At the end of each block, experimenters asked participants to rate their level of physical and mental fatigue on a 7-point Likert scale, to ensure that participants were not under physical tiredness or attentional loss. Also, the room temperature was checked every 30 min, ensuring that it remained stable throughout the whole session.

3.2.4 Data processing and statistical analysis

For each trial, we recorded the real elapsed time and the participant's time estimation.

First, time estimates of each participant were fitted with a 2-parameter linear function (minimum least squares fit) to give individual average estimates as a function of elapsed time. Then, to measure the dependency of estimation uncertainty on duration, for each participant and condition, we calculated the residuals (root mean square errors, RMSE) of time estimation with respect to individual average estimates. At this point, for each condition, we pooled together residuals of all participants, and we averaged them in intervals of 21 seconds. Since the dispersion along the mean increases with time we calculated the error within each bin as $RMSE * (1/\sqrt{2 * N})$. Finally, we fitted binned data with a linear function with 2 parameters (minimum least squares fit). To assess whether RMSE increases with duration we tested whether the slopes of the fitting curves were compatible with zero (z-tests). To investigate whether the trends of RMSE in each task and walking condition were the same, the slopes of the fits have been statistically compared with z-tests.

We then calculated the time difference in seconds between estimated and effective durations (estimation bias). For each cognitive task in the three motor conditions, the estimation biases of all participants were averaged in intervals of 21 seconds and fitted with a 2-parameter linear function (minimum least squares fit). To assess the role of our variables in time estimation, we performed a general linear mixed-effects model (GLMM) pooling estimation biases of all participants together, with bias as the outcome variable, and cognitive task (three levels: easy, medium, hard), motor condition (three levels: forward regular-speed walking, forward irregular-speed walking, and backward irregular-speed walking) and durations (continuous) as fixed effects. We also included the variable *participants* as the random effect. Pairwise post-hoc comparisons between categorical factors were assessed by using *t*-tests with Bonferroni's correction. Post-hoc comparisons between continuous and categorical variables were assessed with *z*-tests.

For the medium and hard tasks, we also measured correct responses and the response times for math operations, to assess possible influences of motor tasks on cognitive performance. The averaged percentages of correct responses and response times were compared with two-

way ANOVA analyses, with factors; motor condition (three levels: forward regular-speed walking, forward irregular-speed walking and backward irregular-speed walking) and task difficulty (two levels: medium and hard). The p-values obtained from post hoc analyses were adjusted using the Bonferroni correction. To account for potential individual differences in cognitive performance, we correlated estimation bias with task performance and reaction times to determine if individual abilities influenced temporal estimation.

To test the retrospective power of our observed effect based on the sample size and parameter estimates derived from the given data set, we performed a post-hoc power analysis for a general linear model (with 3 regressors) using G* Power3 (Erdfelder et al., 2009), by deriving the effect size from R-squared R^2 . Based on the consideration that simpler models are less sensitive than mixed models, we can reasonably infer that the result found with general linear model is valid also for our mixed model.

Matlab (R2018b version) and Excel (16 version) software were used for data processing, data fitting, and graphs' creation. JASP (Version 0.8.6), G*Power (3.1.9.4), and R (4.0.3) software were used for statistical analyses.

3.3 Results

In this study, participants are asked to perform cognitive tasks of different difficulties and estimate durations of up to two minutes, while being concurrently subjected to motor tasks of different difficulties. Raw data from all participants for each cognitive task (easy: looking at the screen; medium and hard: solving simple or hard sum operations) in all motor conditions (forward regular-speed walking, forward irregular-speed walking, and backward irregular-speed walking) are reported in **Figure 14**.

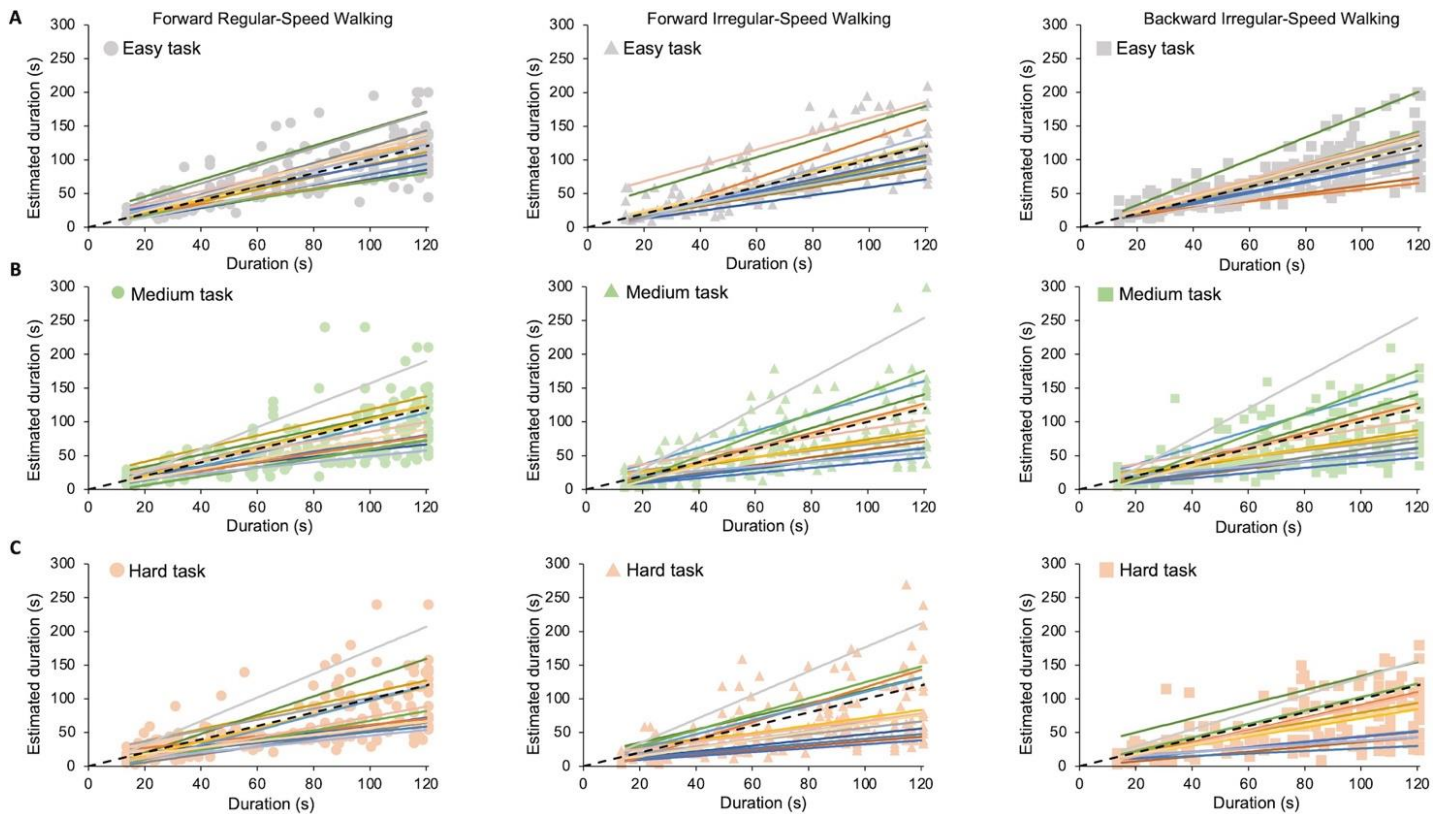


Figure 14. Time estimation in different motor and cognitive tasks. Each colored fit line is the average time estimate of the same participant. Dots indicate the forward regular-speed walking condition (left panels); triangles indicate the forward irregular-speed walking condition (middle panels); squares indicate the backward irregular-speed walking condition (right panels). Dashed black lines represent exact estimations. (A) Easy task. (B) Medium task. (C) Hard task.

A close inspection of **Figure 14** shows that participants behave very differently from each other: individual participants with high (or low) time estimates in one condition tend to maintain high (or low) estimates in all the other conditions (see different color lines in all panels). Therefore, to measure accuracy and precision, we need to take into account individual variability before averaging the data.

In **Figure 15** we then reported root mean square errors (RMSE) with respect to individual average estimates. Statistics show that, for each cognitive task and motor condition, RMSE increases with duration (easy task: forward regular $z = 2.6$, $p = 0.004$; forward irregular $z = 5.6$, $p < 0.001$; backward irregular $z = 5$, $p < 0.001$; medium task: forward regular $z = 3.8$, $p < 0.001$; forward irregular $z = 5$, $p < 0.001$; backward irregular $z = 2.5$, $p = 0.005$; hard task:

forward regular $z = 14, p < 0.001$; forward irregular $z = 6.6, p < 0.001$; backward irregular $z = 3, p = 0.001$). For each walking condition, there are no significant differences between tasks (all $p > 0.05$). We found differences between walking conditions only in the hard cognitive task (forward regular vs. forward irregular: $z = -4.9, p < 0.001$; forward regular vs. backward irregular: $z = 2.6, p = 0.004$; forward irregular vs. backward irregular: $z = -3.9, p < 0.001$).

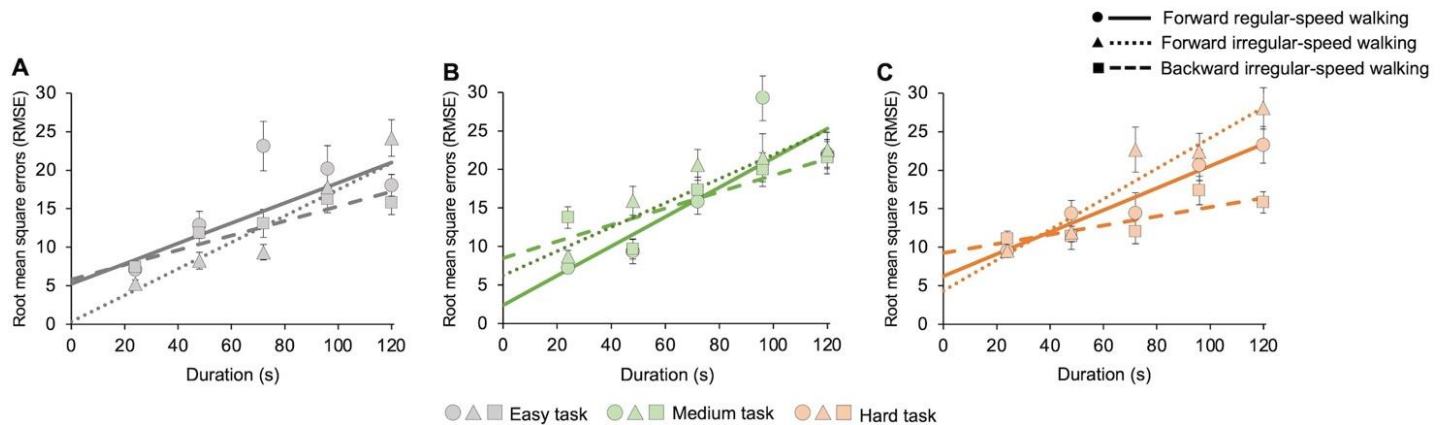


Figure 15. Estimation uncertainty as a function of duration. Estimation uncertainty increases with duration, similarly for each cognitive task and motor condition. The graphs show the root mean square errors (RMSE), computed on 21s intervals, for all cognitive and motor tasks with their best-fit curves. Solid lines and dots represent the forward regular-speed walking condition; dotted lines and triangles represent the forward irregular-speed walking condition; dashed lines and squares represent the backward irregular-speed walking condition. (A) Easy task (number of occurrences in each bin - forward regular walking: 67, 27, 26, 23, 82; forward irregular walking: 63, 29, 44, 37, 52; backward walking: 69, 35, 26, 42, 53). Goodness of fit - forward regular walking: $R^2 = 0.7$; forward irregular walking: $R^2 = 0.9$; backward walking: $R^2 = 0.9$. (B) Medium task (number of occurrences in each bin - forward regular walking: 47, 17, 45, 49, 66; forward irregular walking: 63, 36, 53, 24, 49; backward walking: 48, 29, 53, 42, 52). Goodness of fit - forward regular walking: $R^2 = 0.8$; forward irregular walking: $R^2 = 0.9$; backward walking: $R^2 = 0.7$. (C) Hard task (number of occurrences in each bin - forward regular walking: 72, 37, 15, 53, 48; forward irregular walking: 54, 44, 30, 46, 51; backward walking: 64, 22, 29, 44, 66). Goodness of fit - forward regular walking: $R^2 = 0.9$; forward irregular walking: $R^2 = 0.9$; backward walking: $R^2 = 0.7$.

Regardless of the motor condition, **Figure 14** also shows that temporal estimations tend to be accurate while participants pay attention only to time (easy task, **Figure 14A**), whereas they perceive shorter duration while performing demanding cognitive tasks (medium and hard tasks,

Figure 14B and **Figure 14C**). The estimation biases for each task, averaged across participants, are then reported in **Figure 16**. We conducted a GLMM analysis after pooling estimation biases of all participants together (see Data processing below for details). First, the model reveals a main effect of the cognitive task ($\chi^2(2) = 122.2, p < 0.001$), confirming that the bias depends on its level of difficulty. Pairwise post-hoc comparisons show significant differences between all cognitive tasks (easy vs medium: $t = 7.7, p < 0.001$; easy vs hard: $z = 11.1, p < 0.001$; medium vs hard: $t = 3.2, p = 0.004$). GLMM also reveals a significant effect of duration ($\chi^2(1) = 104.1, p < 0.001$), and a significant interaction between task and duration ($\chi^2(2) = 42.9, p < 0.001$). Underestimation increases with durations only in the medium ($z = -7.2, p < 0.001$, see **Figure 16B**) and in the hard tasks ($z = -9.7, p < 0.001$, see **Figure 16C**). No significant effect of walking emerged ($\chi^2(2) = 2.7, p = 0.2$), indicating that biases do not depend on the difficulty of the walking task. A post-hoc power analysis with effect size $f^2 = 0.49$, alpha = .05, and sample size = 15 returns a power of .81, confirming the appropriate statistical power of the above results.

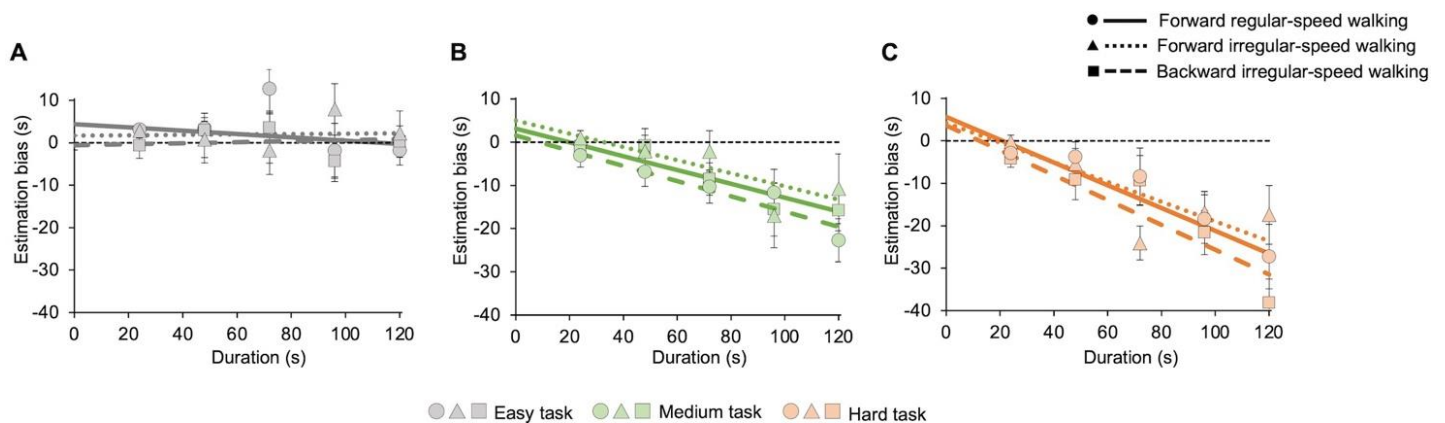


Figure 16. Averaged estimation bias in different motor and cognitive tasks. Underestimation increases with cognitive load but does not change with the difficulty of the motor task. The graphs show the estimation bias, computed on 21s intervals, for all cognitive and motor tasks with their best-fit curves. Error bars are SE across participants. Solid lines and dots represent the forward regular-speed walking condition; dotted lines and triangles represent the forward irregular-speed walking condition; dashed lines and squares represent the backward irregular-speed walking condition. Dashed black lines represent exact estimations. (A) Easy task (forward regular-speed walking: slope = -0.04 ± 0.04 , intercept = 4.4 ± 2.2 ; forward irregular-speed walking: slope = 0.004 ± 0.05 , intercept = 1.7 ± 3.1 ; backward irregular-speed walking: slope = 0.01 ± 0.03 , intercept = -0.6 ± 1.6). (B) Medium task (forward regular-

speed walking: slope = -0.2 ± 0.03 , intercept = 3.1 ± 1.3 ; forward irregular-speed walking: slope = -0.15 ± 0.05 , intercept = 4.9 ± 3.2 ; backward irregular-speed walking: slope = -0.2 ± 0.03 , intercept = 1.6 ± 1.8). (C) Hard task (forward regular-speed walking: slope = -0.3 ± 0.08 , intercept = 5.6 ± 4.2 ; forward irregular-speed walking: slope = -0.2 ± 0.04 , intercept = 4.2 ± 2.8 ; backward irregular-speed walking: slope = -0.3 ± 0.06 , intercept = 3.6 ± 3.1).

Finally, we analyzed correct responses (**Figure 17A**) and response times (**Figure 17B**) to math sums in the medium and hard tasks. In the medium task, the percentage of correct responses averaged over participants and durations is almost 100% for all walking conditions, while in the hard task, the percentage of correct responses drops to about 90% (Figure 17A). ANOVA (two factors: motor condition - three levels: forward regular-speed walking, forward irregular-speed walking, and backward irregular-speed walking - and task difficulty - two levels: medium and hard) confirms that correct responses differ across the two cognitive tasks ($F(1,14) = 12.3, p = 0.003, \eta^2 = 0.3$) but they do not depend on the motor condition ($F(2,28) = 0.7, p = 0.4, \eta^2 = 0.008$). In the hard task, response times averaged over participants and durations are almost double than in the medium task for all walking conditions (Figure 17B). ANOVA confirms that response times depend on the cognitive tasks ($F(1,14) = 122.1, p < 0.001, \eta^2 = 0.9$) but not on the motor condition ($F(2,28) = 0.5, p = 0.6, \eta^2 = 0$). In addition to the primary analyses, we also examined the relationship between estimation bias and individual performance across tasks. Correlations between estimation bias and reaction times, as well as task performance, were all weak, indicating that individual differences did not substantially influence temporal estimation.

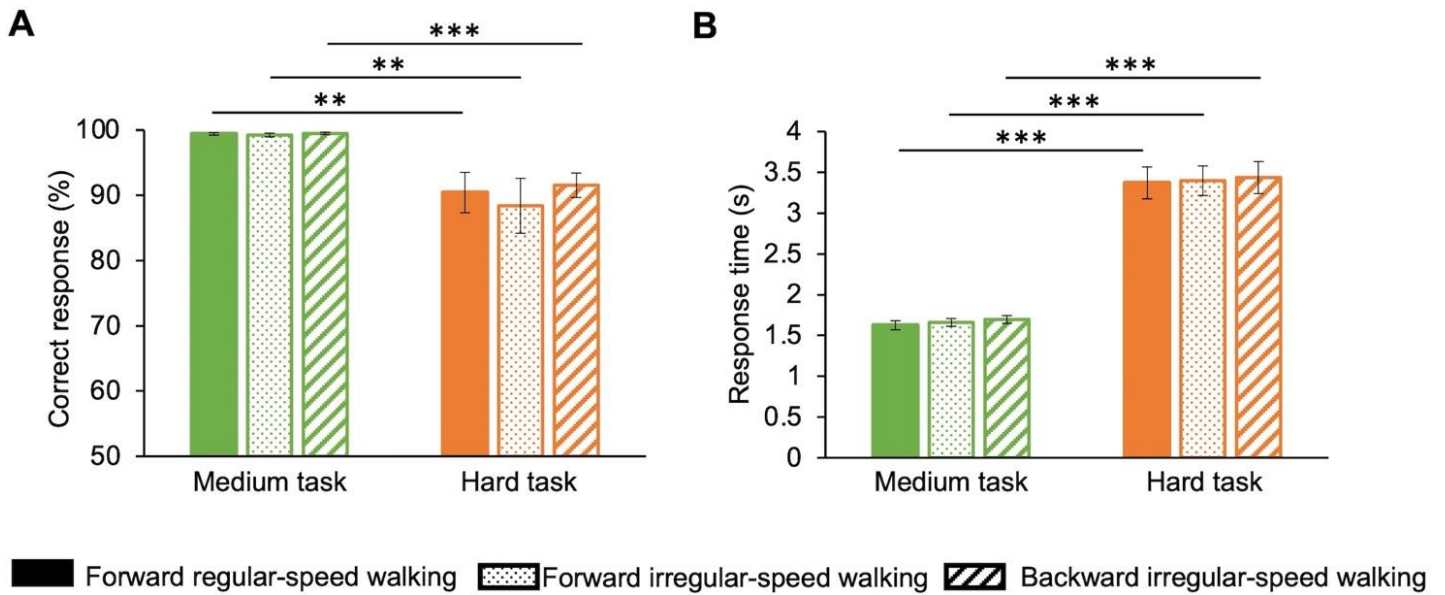


Figure 17. Performance for math operations in the three motor conditions. Correct responses and reaction times change with cognitive load but do not change with the difficulty of the motor task. Green: medium task; orange: hard task. Solid bars correspond to the forward regular-speed walking; dotted bars correspond to the forward irregular-speed walking; striped bars correspond to the backward irregular-speed walking. (A) Percentage of correct responses. (B) Response times. Asterisks mark statistically significant differences with ANOVAs: ** $p < 0.01$, *** $p < 0.001$. Error bars are SE across participants.

3.5 Discussion

Time estimation has been extensively studied for well over a century but the way in which we code temporal information is still little understood. Several pieces of evidence show that time estimation depends on many contextual variables and is distorted by concurrent cognitive and motor tasks (Baldauf et al., 2009; R. a. Block, 2003; R. A. Block et al., 2010; R. a. Block & Zakay, 2008; Buhusi & Meck, 2005; Grondin, 2010; Ivry & Schlerf, 2008; Matthews & Meck, 2014, 2016; Merchant et al., 2013; Sucala et al., 2010; Wittmann, 2009).

In our previous study (Castellotti et al., 2022), walking induced a higher estimation uncertainty and a larger underestimation of long durations only during the execution of demanding cognitive tasks, with respect to the sitting condition. We speculated that the motor task increases somehow the weight of the concurrent cognitive effort, leading to additional openings of the switch and, consequently, to a lower number of accumulated pulses than in sitting conditions (Castellotti et al., 2022). In this previous work, however, we compared a

relatively automatic motor condition with a condition where motion was absent, therefore the cognitive loads due to the motor tasks were relatively lower than those due to the mental tasks and therefore not quite comparable.

For this reason, in the present study, we manipulated the difficulty of the motor task, setting an automated body movement that requires no motor or mental effort (Bridenbaugh & Kressig, 2011; Clark et al., 1601; Paul et al., 2005) (forward regular-speed walking), a more difficult movement requiring some motor control and body balance due to unpredictable speed changes (forward irregular-speed walking), and a highly demanding movement requiring continuous motor control to adapt to random speed changes (backward irregular-speed walking). We can reasonably assume that these different types of walking require a progressive increase of attentional load. We also combined these motor tasks with three cognitive tasks of increasing difficulty.

Our purpose was to investigate the influence of motor and cognitive task difficulty on time estimation. We assume that walking activity, as well as other mental tasks, need allocation of attention (Malouin et al., 2003) and therefore might affect temporal judgments with increasing distortions as a function of its difficulty, as predicted by the *attentional allocation model* (Allman et al., 2014; Grondin, 2010; Matthews & Meck, 2016). That is, walking activity could independently act on the switch to alter the number of pulses transferred to the accumulator (“Funct. Neural Mech. Interval Timing,” 2003; Gibbon, 1977; John H Wearden, 2003).

We first measured estimation uncertainty, finding that, according to the *scalar timing theory* (“Funct. Neural Mech. Interval Timing,” 2003; Gibbon, 1977; John H Wearden, 2003), it increases linearly with time. The increase of variability with duration is the same for all cognitive tasks. In the easy and in the medium cognitive tasks, uncertainties do not vary with motor conditions. In the hard cognitive task, uncertainties differ between motor conditions, being highest for forward irregular walking. This effect could be due to the higher speeds of walking involved in this condition (Karşilar et al., 2018).

We then analyzed estimation accuracy by measuring the estimation bias. The results confirm that the difficulty of the cognitive task affects estimation, with increasing underestimation with task difficulty (Castellotti et al., 2022; Polti et al., 2018). The trend of the estimation bias is

also in line with previous findings: in the easy task, estimation bias remains constant across durations (Castellotti et al., 2022; Polti et al., 2018), while in harder tasks underestimation scales with durations, so that the longer durations were more underestimated than the shorter ones (Castellotti et al., 2022; Matthews & Meck, 2016; Polti et al., 2018). Time distortions induced by mental calculation might depend on the role of the right parietal cortex, which is consistently implicated in mathematical cognition (Wu et al., 2009), and time estimation (Hayashi et al., 2018). We did not find evidence of any effect of motor tasks on temporal judgments, even in the most demanding one, independently of the presence or absence of a concurrent cognitive task.

Particularly, even the continuous attention needed to perform a demanding non-automatic walking task alone does not seem to be able to alter the counting of time, as other cognitive tasks do (Brown, 1997; Polti et al., 2018). A possible explanation could be that the neural mechanisms involved in walking are not able to directly open the switch, that would produce a loss of pulses and thus a decrease in the perceived duration, as predicted by the *scalar timing theory* (“Funct. Neural Mech. Interval Timing,” 2003; Gibbon, 1977; John H Wearden, 2003). Alternatively, our non-automatic walking, although irregular and backward, might require a much smaller amount of attention than that needed by other mental tasks, as those involving working memory or arithmetic operations.

Since we did not find evidence of differential effects induced by diverse types of walking on temporal judgments, it has not been possible to study the nature of the interactions between motor and cognitive processes on time estimation.

The results of the current study are hard to frame in the existing literature on time estimation during motor activity. Few studies are not in line with the *attentional allocation model*, finding an overestimation of temporal durations during walking, and suggest that walking speeds up the internal clock, probably due to its physiological effects (Kroger-Costa et al., 2013; Sayali et al., 2018). However, they used non-ecological paradigms for the study of time estimation, either using very short durations (much less than 1 second; (Kroger-Costa et al., 2013)) or reproduction methods (Sayali et al., 2018). Therefore, their results are hardly comparable to ours. Other studies, instead, have found duration underestimation of short intervals (in the

order of *ms*) induced by hand movements (Tomassini & Morrone, 2016; Yokosaka et al., 2015; Yon et al., 2017), suggesting that this particular motor activity is able to decrease attention to time, serving as secondary task. The difference with our results could be then explained by the fact that fine movements involve different motion circuits (Tomassini & Morrone, 2016) and probably require a larger attentional load than gross body movements like walking. In future studies then, one should use more complex motor actions (e.g., reproducing hand movements sequences), in the absence of other cognitive tasks to verify that time underestimation is replicated also at longer time intervals (in the order of *secs*), and with a concurrent cognitive task to uncover possible interaction between them.

Although cognitive performance is deteriorated by demanding postural or walking tasks (Castellotti et al., 2022; Shumway-Cook & Woollacott, 2000), here we did not find any effect of different walking types either on the number of correct responses or time responses. This result might further suggest that the manipulation introduced here, however effective it may seem in making the motor task difficult and non-automatic, is mostly ineffective at influencing the subject's responses. It is difficult to directly compare the results of this study with those from Study 1, as in this case, our baseline was regular walking rather than a sitting condition. The sitting condition might have better highlighted the impact of motor activity, but it wouldn't have allowed us to assess differences between various motor activities. The motor task manipulation seemed ineffective not only with respect to temporal estimation but also regarding the resolution of math problems. As for the walking speed, the variation in speed across conditions did not significantly impact the results. The main focus was on maintaining the overall pace in each condition, and when controlling for physical fatigue, no differences were found between participants in the various conditions. This suggests that, despite the differences in walking speed, the cognitive load induced by the motor activity was consistent across all subjects.

To conclude, from our results we can infer that executing walking tasks, even demanding as walking backward at an irregular randomly-changed speed, cannot be considered in the same way as other demanding cognitive tasks, like solving hard operations (Castellotti et al., 2022) or memorizing past items (Polti et al., 2018), in distorting time estimation.

Chapter 4

The influence of task engagement on time perception

4. The influence of task engagement on time perception

4.1 Introduction

This research is further developed in our third study, where we focus specifically on the nuances of task complexity and difficulty in relation to time perception. Numerous models have been proposed to elucidate the mechanisms underlying time perception, reflecting the complex interplay of cognitive, neural, and environmental factors (R. a. Block, 2003; Grondin, 2010; Matthews & Meck, 2014; Merchant et al., 2013; Wittmann, 2009). These models underscore the multifaceted nature of time perception, each offering unique insights into how we perceive the temporal dimensions of our surroundings.

Several studies have also explored how shifts in attentional focus, particularly during secondary tasks, affect time perception. Despite the breadth of research on time perception during cognitive tasks, a significant gap remains in understanding how individuals estimate time in a more ecological situation, when no predefined time structure is present. Most studies have employed fixed time intervals, typically within a limited range (Castellotti et al., 2022; D'Agostino et al., 2023; Macar et al., 1994b; Polti et al., 2018; E. C. Thomas & Brown, 1974; Zakay & Tsal, 1989), and much of the literature has focused on very short durations (for a review, see (R. A. Block et al., 2010; Buhusi & Meck, 2005; Matthews & Meck, 2014)). In these studies, when the authors refer to task difficulty, they often use the terms "difficulty" and "complexity" interchangeably, but the literature acknowledges a distinction between these two constructs (for a review see (P. Liu & Li, 2012)). The use of predefined intervals limits the ability to differentiate the distinct roles of complexity and difficulty in time perception. Task complexity refers to the inherent cognitive demands of a task, involving the mental effort required to process and manage various elements of the task. It is associated with the cognitive resources needed to complete the task effectively, such as working memory and executive functions (Bedny et al., 2012; Braarud, 2010; Evangelisti et al., 1986). Conversely, task difficulty pertains to the extent to which a task challenges an individual based on their personal

resources, including their prior knowledge, skills (Bedny et al., 2012; Braarud, 2010; Evangelisti et al., 1986; P. Liu & Li, 2012; Robinson, 2001)..

This distinction is crucial for comprehending how cognitive and neural factors contribute to the subjective experience of time in relation to different types of cognitive demands. Given this distinction, our primary question is: is time estimation influenced by task complexity or task difficulty?

To answer it, here we employed two different cognitive tasks—visual search with an increasing number of distractors or decreasing their contrast and mathematical sums with increasing number of addends—to probe independently the effect of both complexity and difficulty on time perception. Participants estimated the time spent on each task, allowing us to separate actual time from perceived time. By not imposing fixed durations, we captured the effective time required to complete the tasks, reflecting the impact of difficulty. Fixed intervals can distract participants, leading them to focus on both the task and the passage of time, which may artificially influence their performance. In contrast, without such constraints, participants can fully engage in the task, enabling us to measure their cognitive engagement, an essential aspect of task complexity (P. Liu & Li, 2012). This innovative approach allows for the evaluation of how time perception in quantitative terms varies under more ecologically valid conditions, offering new insights into the cognitive mechanisms underlying time perception.

4.2 Materials and Methods

4.2.1 Participants

A total of 87 young adults (average age = 23.7 years, SE = 0.5) participated, including 34 in the main visual search experiment, 21 in the contrast-experiment, and 32 in the mathematical sums experiment. All participants were university students, unaware of the study's purpose, and provided written informed consent. They completed a questionnaire on personal information, expertise, sleep habits, vision, and cognitive health. Participants had normal or corrected-to-normal vision, no medication intake, no brain damage, and were free of cognitive

disorders. They reported a regular sleep-wake cycle (average sleep duration of 7.3 ± 0.2 hours), and none were professional athletes or musicians.

4.2.2 Procedure and conditions

Participants were tested individually in a dark room with stimuli displayed on a 27-inch AGOC gaming monitor (100Hz, 1920x1080 resolution) using Psychophysics Toolbox for Matlab (2018b, Mathworks, Natick, MA). Each experiment had two conditions: a control condition and an experimental condition, randomized and divided into block sessions. This design allowed us to directly compare time estimates during task engagement versus non-engagement for each individual.

Regarding the experimental conditions, in the main visual search experiment (125 trials), participants were asked to search a letter target embedded among repeated distractors (**Figure 18A**). Given cognitive load in visual search tasks escalates logarithmically with the number of distractors (Treisman & Gelade, 1980), the visual stimuli varied in numerosity (100, 200, 300, 400, 500) that comprised, for example, 99 distractors and 1 target letter, with random rotations spanning from 0 to 359° . In the contrast-experiment, visual search task (125 trials) was among a fixed number of distractors (300), and we varied the contrast between 0.05, 0.1 and 1, following the Michelson's formula.

In the mathematical sums experiment, participants were instructed to solve mathematical sums of varying difficulty (**Figure 18B**, “solve simple”, involving 1-digit numbers with 2, 3, and 5 addends, and a “solve hard” task with 2-digit numbers featuring 2, 3, and 5 addends, including carryover). To moderate difficulty, numbers ranged from 1 to 49, excluding those ending in zero (e.g., twenty, ten) to avoid overly simplistic operations. Additionally, we varied the number of addends alongside the digit numbers to create a spectrum of effective solving times. For instance, the “solve simple” task could include operations like $1+4$ or $1+4+6+7+3$, which require varying durations to complete. Participants performed 60 trials for solve simple and 60 trials for solve hard task.

On the other hand, the control condition was used as baseline perception of time for each participant during periods of non-engagement in tasks (**Figure 18C**). Participants were instructed to fixate on a small point at the center of the screen (a $2 \times 2^\circ$ grey circle). The durations for this condition varied between 1 and 80 seconds and they were determined based on a preliminary study where we analyzed the time distribution of the main visual search task, averaging the durations associated with each distractor.

Before each trial, instructions were displayed until the space bar was pressed. A green circle ($2 \times 2^\circ$) indicated the trial start. Participants responded by clicking on the target letter or solving sums and pressing the space bar to input results. After the trial, a red circle indicated the end, and participants estimated the trial duration using a "time ruler" displaying three scales for seconds (0-60 seconds).

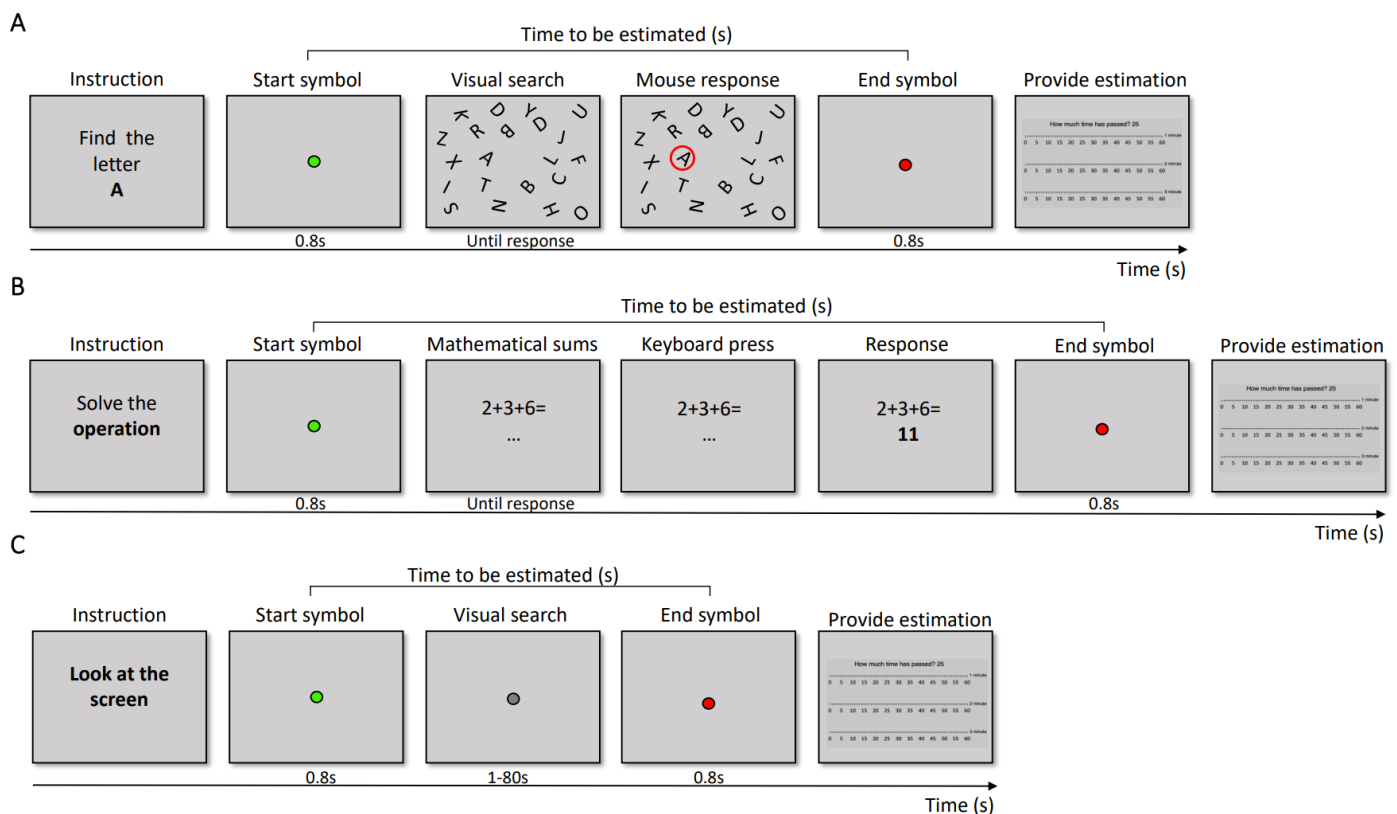


Figure 18. Procedure and cognitive task. (A) Visual search task. (B) Mathematical sums task. (C) Control task. The green circle indicates the beginning of time estimation; the red circle indicated the stop of time estimation.

4.2.3 Data processing

In each trial across all experiments, we recorded both the effective time to complete the task and the time estimation provided by the participant, allowing us to calculate the estimation bias as the difference between these values. A power analysis was performed through the G*Power software using an ANOVA design, which is an approximation method for our analyses (F tests family, repeated measures – within factors). We used, as input parameters, an effect size $f = 0.2$, alpha level = .05, and correlation among repeated measures = 0.5.

We conducted a linear mixed-effects model (LMM) analysis to pool estimation biases across all participants. The outcome variable was estimation bias, with cognitive task and effective time as fixed effects. Participant identity was included as a random effect to account for individual variability. Finally, we compared the slopes obtained from the model using z-tests across all experiments to investigate whether differences in time estimation were based not only on the difficulty of the same task but also on the type of task.

Since our data did not follow a Gaussian distribution, the Wilcoxon signed-rank test was utilized to compare the medians of the effective time between conditions and, finally, we measured the correct responses for all experiments to ensure that participants' attention was directed to the tasks. The average percentages of correct responses were compared using paired-sample t-tests, and the p-values were adjusted using the Bonferroni correction. To account for potential individual differences in cognitive performance, we correlated estimation bias with task performance and reaction times to determine if individual abilities influenced temporal estimation. Matlab (R2018b) and Excel (version 16) were used for data processing, data fitting, and graph creation. JASP (version 0.8.6) and R (version 4.0.3) software were used for statistical analyses.

4.3 Results

4.3.1 Visual search experiments

In the visual search experiment with varying numbers of distractors, underestimation of time significantly increases with both effective time ($\chi^2(1) = 2345.8$, $p < 0.001$) and task ($\chi^2(5) =$

514.7, $p < 0.001$, **Figure 19A – left panel**). However, post-hoc comparisons reveal that significant differences emerge only between the no-cognitive task and the cognitive task (all p -values < 0.001), while the estimation bias slopes do not depend on the number of distractors (all p -values > 0.05). Notably, the effective time spent on the task increases as the number of distractors increases (on average, $W(30)=60$, $p < 0.001$, **Figure 19A – right panel**). while performance remains high, averaging $96\% \pm 0.6\%$ (SE).

Similar results were observed when reducing the contrast while maintaining a fixed number of distractors (300). In this case, underestimation increases significantly with effective time ($\chi^2(1) = 407.1$, $p < 0.001$) and task ($\chi^2(3) = 321.1$, $p < 0.001$, **Figure 19B – left panel**), but again, only in comparisons between the no-cognitive and cognitive tasks. Estimation bias slopes remained unaffected by contrast difficulty levels (all p -values > 0.05). The effective time spent on the task is significantly longer with 5% contrast stimuli than with 100% contrast stimuli (**Figure 19B – right panel**, $W(18) = 118$, $p < 0.05$). Performance remains consistent, with an average accuracy of $95\% \pm 1.5\%$ (SE).

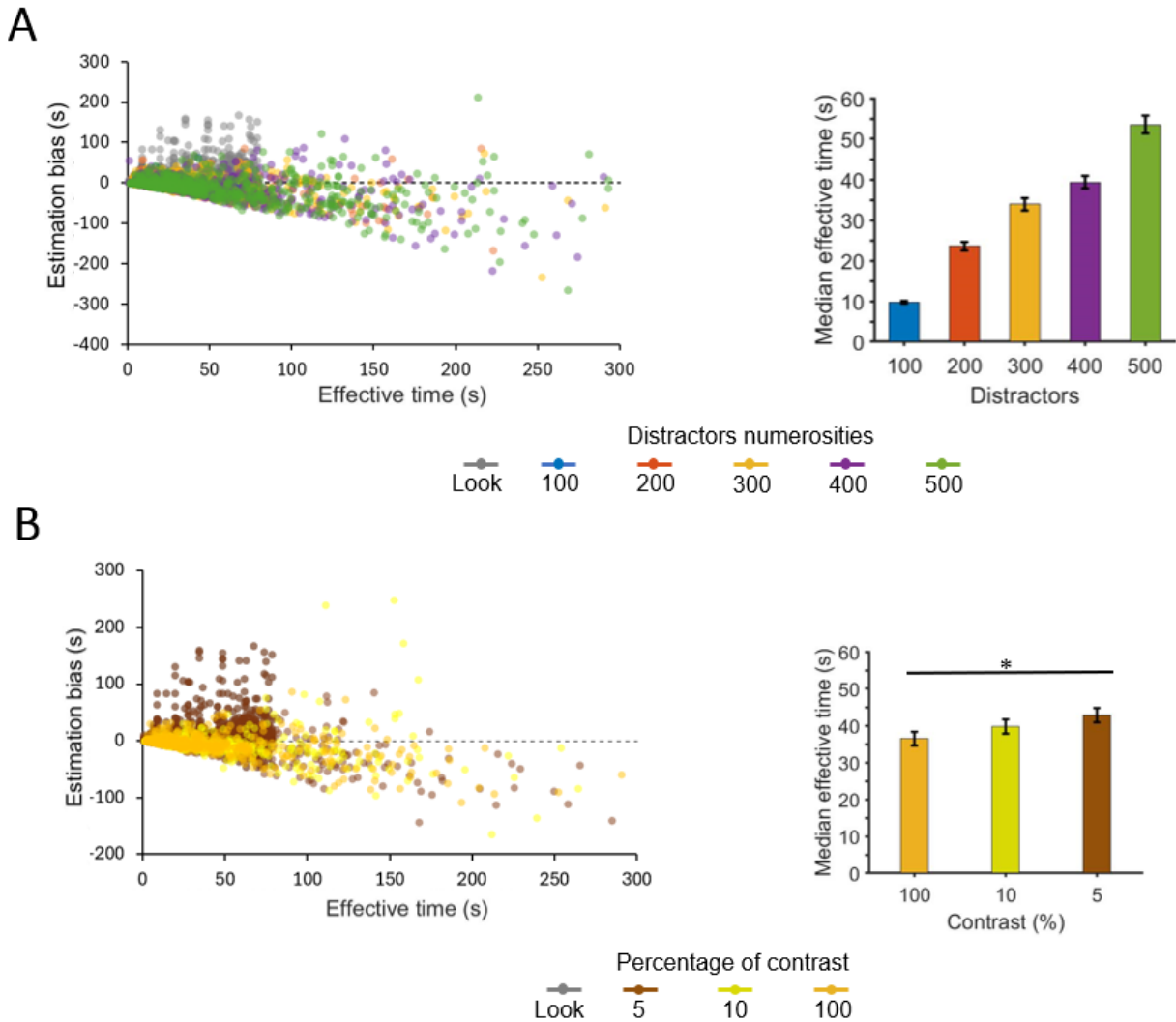


Figure 19. Estimation bias and median effective time in visual search experiments. . The left panels show estimation bias in seconds as a function of effective time for different look tasks and distractor numerosities (A) and contrast levels (B) illustrated up to 300s for clarity. The right panels illustrate the median effective time for each distractor numerosity, all p values < 0.001 (A) and contrast level (B). Error bars indicate standard errors.

4.3.2 Mathematical sums experiment

In the mathematical sums experiment, underestimation increases with effective time ($\chi^2(1) = 171.8, p < 0.001$) and task ($\chi^2(5) = 112.3, p < 0.001$, **Figure 20 – left panel**). Even in this case, significant differences are present only between the no-cognitive task and the cognitive task (all p values < 0.001) with no significant differences in estimation bias based on the difficulty of the arithmetic operations (all p values > 0.05). As found in the visual search experiment, the effective time increases as the difficulty of the sums increases ($W(31) = 0, p < 0.001$,

Figure 20). Performance is approximately $97.1\% \pm 0.6\%$ in solve simple task and $86.6\% \pm 1.4\%$ in solve hard task (simple vs hard: $t(62) = 7.1, p < 0.001$). In addition to the primary analyses, we also examined the relationship between estimation bias and individual performance across tasks. Correlations between estimation bias and reaction times, as well as task performance, were all weak, indicating that individual differences did not substantially influence temporal estimation.

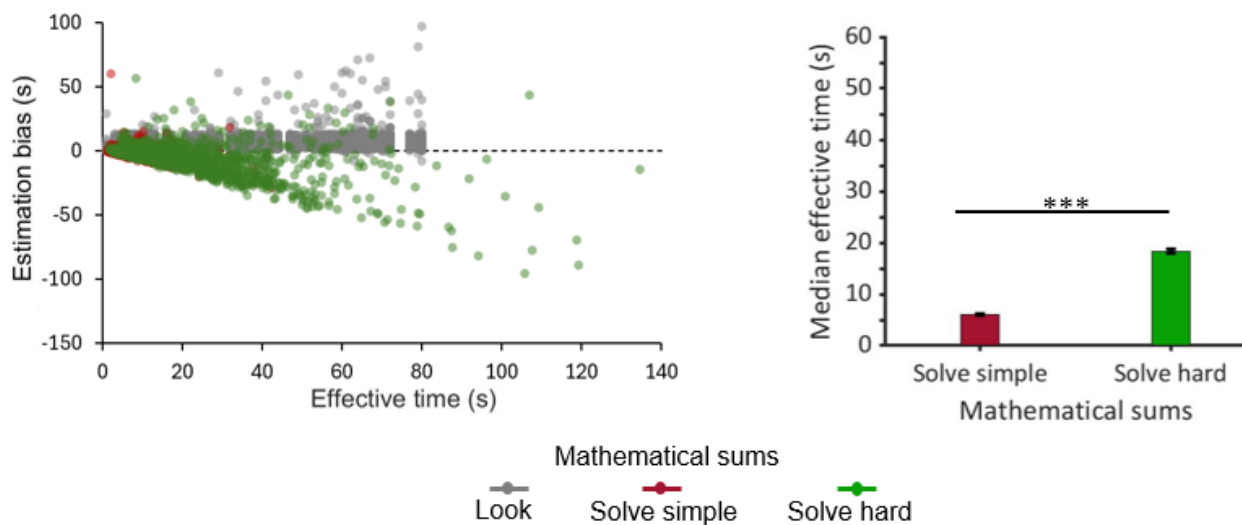


Figure 20. Estimation bias and mean effective time in mathematical experiment. The panel illustrates the median effective time for each mathematical sum. Error bars indicate standard errors.

A comparison of all the estimation bias slopes reveals that the underestimation during cognitive tasks is statistically the same independently of the number of distractors or contrast value ($z = -1.9, p > 0.005$). On the other hand, the underestimation during the mathematical sums is statistically larger compared to the visual search tasks (full contrast vs. sums: $z = 6.2, p < 0.001$; low contrast vs. sums: $z = 13.2, p < 0.001$). Notably, the average underestimation for the visual search task is approximately 25%, while it reaches around 40% for the mathematical sums task, indicating that time estimation is influenced more by the type and complexity of the task rather than its difficulty (**Table 2**).

Task	Conditions	Estimation bias slopes
Visual search with increasing distractors	Look	0.06 ± 0.01
	100	-0.16 ± 0.05
	200	-0.24 ± 0.02
	300	-0.26 ± 0.02
	400	-0.31 ± 0.02
	500	-0.28 ± 0.01
Visual search with decreasing contrast	Look	0.1 ± 0.01
	5	-0.21 ± 0.02
	10	-0.18 ± 0.02
	100	-0.20 ± 0.02
Mathematical Sums	Look	0.12 ± 0.005
	simple	-0.37 ± 0.02
	hard	-0.41 ± 0.01

Table 2. Estimation bias slopes and standard errors for all experiments.

4.4 Discussion

Time estimation has been extensively studied for over a century, yet the mechanisms underlying how we code temporal information remain not fully understood. Numerous studies have shown that time estimation can be influenced by various contextual variables and is often distorted by concurrent cognitive tasks (Brown, 1985; Castellotti et al., 2022; Polti et al., 2018; Zakay & Block, 1996).

In this study, we introduced a novel paradigm to investigate how the complexity and difficulty of two distinct cognitive tasks—visual search and mathematical sums—influence time perception. We found that underestimation is influenced by the specific task at hand, whereas task difficulty only affects the effective time spent doing the task, even when the difficulty consists in a drastic reduction of stimulus contrast.

Specifically, in visual search experiments, participants consistently underestimated time duration during task engagement, consistent with the attentional allocation model (Allman et al., 2014; Grondin, 2010; Matthews & Meck, 2016). Visual search tasks are multifaceted, involving both perceptual and cognitive dimensions. Perceptual factors such as the number of

distractors, their similarity to the target, and the visual contrast of stimuli play critical roles (Lavie, 1995; Treisman & Gelade, 1980). Cognitive load, on the other hand, encompasses the mental effort required for tasks such as target identification, decision-making, and maintaining task objectives within working memory (Chun, 2000; Jeremy M. Wolfe, 1994). Significant estimation differences across contrast levels would have suggested that perceptual load, rather than solely cognitive load, plays a role in our experimental tasks. Our findings revealed that time underestimation remains consistent during visual search tasks across varying difficulties, regardless of the number of distractors or significantly reduced visual contrast, with an approximate underestimation of 30%. Similarly, in our mathematical sums experiment, we found no significant differences in time underestimation between simple and hard sums, with an underestimation of around 50%.

Previous research indicated that more difficult task led to greater time underestimation (Castellotti et al., 2022; D'Agostino et al., 2023; Ebersbach et al., 1995; Polti et al., 2018). However, in all these paradigms, the use of fixed durations presents a confounding issue because it does not allow for an accurate measurement of the actual time spent completing the tasks. This makes it difficult to distinguish between task difficulty and complexity. In contrast, our current findings suggest that, by not using fixed time intervals, participants may have been more focused on the task itself, leading to a more precise measure of the internal clock rate across varying difficulty levels. We observed that task difficulty primarily affects the time taken to complete the task, extending it.

Interestingly, the clock rate during the performance of mathematical sums is even slower than that observed during visual search tasks, with a difference in underestimation of approximately 15%, despite participants spending more time on average to complete the visual search tasks. This experimental observation further underscores the distinction between task complexity and task difficulty, which modulates different dimensions of time perception. It has largely known that visual search tasks primarily engage regions of the brain associated with visual processing and attention, such as the occipital lobe, parietal lobe, and dorsal stream (Corbetta & Shulman, 2002). These tasks involve rapid and automatic processes like visual scanning,

feature integration, and spatial attention (Treisman & Gelade, 1980; J M Wolfe et al., 1989; Jeremy M. Wolfe, 1994). On the other hand, mathematical sums tasks impose heavier demands on executive functions and working memory (Baddeley, 2002), engaging regions such as the prefrontal cortex and parietal lobes (Ashcraft, 1992; Dehaene et al., 1999). Neuroimaging studies highlight the critical role of the prefrontal cortex in executive functions and working memory, linking these processes to time perception and estimation (Lewis & Miall, 2003; Wittmann, 2009). Given that task complexity pertains to the inherent cognitive demands and mental effort required to perform a task, the heightened activation of specific brain regions during mathematical tasks may contribute to their greater complexity compared to visual search tasks. This increased complexity and the possible recruitment of different brain regions directly could explain the observed slowing of the internal clock, which corresponds to a greater diversion of attention with respect to the passage of time.

In conclusion, our findings underscore the critical importance of differentiating between task complexity and task difficulty when studying time perception. Complexity pertains to the inherent cognitive demands of a task and its impact on the internal clock, whereas difficulty is related to the resources an individual brings to the task. Our study suggests that complexity is the primary factor influencing time estimation. Specifically, the nature of the task—whether it is more or less complex—affects how time is perceived, rather than the difficulty of the task itself. Mathematical sums tasks are more complex than visual search task, which rely predominantly on visual processes, and heavily engage executive functions, potentially disrupting the internal clock more significantly.

This study, through the introduction of a specific new paradigm, allows for the measurement of the clock rate during the performance of cognitive tasks and can serve as a valuable tool for comparing the complexity of various tasks. Thus, by using time perception as a metric, we can compare different types of tasks—such as linguistic, motor, mathematical, and perceptual—and gain insights into their relative complexity. Future research should focus on exploring the neural bases of these differences and examining how different cognitive loads across diverse

tasks impact time perception. Employing neuroimaging techniques could provide more detailed insights into the neural correlates of these processes.

Chapter 5

General discussion

5. General discussion

5.1 Overview of the findings

The research presented in this dissertation provides a comprehensive exploration of how time perception is shaped by cognitive load, motor activity, and task complexity. Across three studies, we investigated the mechanisms that underlie temporal estimation in diverse contexts, with a particular focus on how simultaneous motor and cognitive demands influence the subjective experience of time.

The first study examined how performing simultaneous motor and cognitive tasks affects time estimation. Our findings demonstrated that as cognitive load increases, participants tend to underestimate the passage of time, particularly when motor tasks are involved. This aligns with the literature suggesting that increased cognitive demands lead to significant time underestimation (Polti et al., 2018; Macar et al., 1994a). The interaction between cognitive complexity and motor demands suggests a competition for attentional resources, resulting in distorted time perception. These results support the Attentional Allocation Model, highlighting how shared attentional resources between cognitive and motor systems contribute to time estimation inaccuracies (Brown & West, 1990; Zakay & Block, 1996). Importantly, the study showed that motor activity exacerbates time underestimation, pointing to the role of shared attentional resources between cognitive and motor systems. The distinction between cognitive factors and motor activity in time perception becomes particularly relevant when considering their effects on longer temporal scales. While sensorimotor tasks primarily involve short-duration timing mechanisms, such as those mediated by the cerebellum and basal ganglia (Grondin, 2010; Merchant et al., 2013), longer intervals (on the order of minutes) require additional engagement of the prefrontal cortex and posterior parietal cortex. These regions integrate attentional and contextual information to support reconstructive processes necessary for extended temporal estimation (Coull et al., 2015; Wittmann, 2009). Furthermore, motor activity's influence on longer intervals may arise from a combination of attentional diversion and embodied cognition. Repetitive motor actions, for example, can create rhythmic patterns that serve as temporal anchors, which may compress or expand perceived durations depending

on their regularity (Repp & Su, 2013). The embodied cognition framework suggests that motor activity grounds cognitive processes, shaping temporal judgments through bodily engagement (Wilson, 2008).

In our second study, we focused on time estimation during motor tasks, comparing how different levels of cognitive and motor complexity influenced temporal judgments. The results revealed that while cognitive load has a profound impact on time underestimation, motor complexity played a relatively smaller role than initially expected. This suggests that time perception is more sensitive to cognitive demands than to motor activity alone, even in situations where physical tasks like walking are involved. These conclusions are consistent with existing literature on dual-task paradigms, which demonstrate that engaging in concurrent cognitive tasks often leads to distortions in perceived time (Brown, 1985; Castellotti et al., 2022; Zakay & Tsal, 1989). Additionally, previous studies have indicated that while walking can interfere with cognitive performance, the extent of this interference is often context-dependent and varies based on the complexity of the tasks involved (Castellotti et al., 2022; Lindenberger, 2000). This finding highlights the primacy of cognitive load in shaping time perception and suggests that the brain may prioritize cognitive processing over motor demands when estimating time. Interestingly, clinical research has shown that disruptions in motor activity, such as those observed in patients with Parkinson's disease, can impair temporal accuracy for both short and long durations (Grondin, 2010; Merchant et al., 2013). This highlights the role of dopaminergic modulation in the basal ganglia, which influences the internal clock and contributes to both motor and cognitive timing processes. The simultaneous engagement of motor and cognitive systems may therefore reflect a dynamic allocation of neural resources, particularly in tasks requiring extended attention to time.

Our third and final study introduced a novel paradigm to explore how task complexity and difficulty influence time perception. We employed two distinct cognitive tasks—visual search and mathematical sums—and investigated the effects of task difficulty (manipulated through the number of distractors or contrast levels in visual search and the complexity of sums). The results indicated that cognitive load leads to time underestimation, regardless of task difficulty,

which primarily affects the actual time spent on the task rather than the perceived duration. Visual search tasks, despite involving complex perceptual and cognitive processes, resulted in less pronounced time underestimation than mathematical tasks, which are more cognitively demanding. These findings support the hypothesis that task complexity, rather than difficulty, plays a central role in modulating time perception. The lack of significant differences in time estimation between simple and difficult versions of both tasks challenges previous literature, which often conflated complexity with difficulty, particularly in paradigms using fixed time intervals. By avoiding pre-defined durations, our novel approach allowed participants to engage more naturally with tasks, offering a more precise measure of how cognitive demands influence the internal clock. We observed that task difficulty primarily impacts the time required to complete the task, not the perceived time, underscoring the distinction between task complexity—the cognitive effort a task demands—and task difficulty—the individual’s ability to handle these demands. Importantly, mathematical sums, which involve higher executive function demands and working memory, produced greater time underestimation than visual search tasks. This distinction aligns with neuroimaging studies suggesting that mathematical tasks recruit prefrontal cortex regions, which are closely linked to executive functions and working memory—both crucial for modulating time perception (Ashcraft, 1992; Baddeley, 2002; Lewis & Miall, 2003; Wittmann, 2009). Interestingly, we observed that the internal clock rate during mathematical tasks was even slower than during visual search tasks, leading to an underestimation difference of approximately 15%, despite longer completion times for visual searches. These conclusions contribute to a growing body of evidence that task complexity is a more reliable predictor of time underestimation than task difficulty. Our findings highlight that complexity—the intrinsic cognitive demands of a task—has a more direct influence on the internal clock and temporal judgment, while difficulty mainly extends the time it takes to complete a task without necessarily distorting perceived time. This distinction is crucial for understanding how different cognitive tasks, such as linguistic, motor, mathematical, and perceptual tasks, affect time perception (Corbetta & Shulman, 2002; Ebersbach et al., 1995; Gibbon, 1977; Zakay & Tsal, 1989).

These results also have broader implications for clinical contexts and human-computer interaction (HCI). In clinical settings, integrating motor tasks with cognitive rehabilitation strategies could enhance temporal accuracy and attentional control, particularly for individuals with basal ganglia dysfunctions such as Parkinson's disease (Grondin 2010; Rammsayer 2008). In HCI, optimizing user experience by reducing cognitive load and leveraging predictable temporal feedback could improve both performance and temporal awareness in interactive systems. For instance, gamified rehabilitation tools that use rhythmic cues to synchronize motor activity with cognitive tasks may exploit embodied cognition principles to enhance engagement and outcomes (Repp & Su, 2013; Hayashi et al., 2018).

5.2 Conclusions

The research presented in this dissertation sheds light on the intricate relationship between time perception, cognitive load, and motor activity. The findings confirm that cognitive load significantly affects time estimation, with increased cognitive demands leading to systematic distortions in how time is perceived (R. a. Block, 2003; Brown, 1985; Brown & West, 1990). High cognitive load diverts attentional resources away from the processing of temporal information, resulting in the underestimation of time. This supports the attentional gate model, which remains a robust framework for understanding how attentional allocation influences temporal judgments (Macar et al., 1994a; Polti et al., 2018). The studies on visual search tasks and mathematical sums further reinforce this idea, showing that time underestimation persists across different types of cognitive tasks, regardless of task difficulty. This suggests that the complexity of the task, rather than its difficulty, plays a central role in influencing time perception. Motor activity also plays a critical role in modulating the perception of time (Buetti et al., 2008; Coull et al., 2004). No-automatic motor tasks, which require higher levels of coordination and cognitive engagement, tend to result in greater inaccuracies in time estimation. This aligns with the hypothesis that motor tasks and cognitive tasks compete for shared attentional resources, leading to potential disruptions in temporal judgments (Merchant et al., 2013). The integration of cognitive and motor processes was found to have a more pronounced effect on time perception, with the simultaneous engagement of these two systems

leading to larger distortions in perceived time. These findings highlight the overlapping neural resources that are shared between cognitive and motor tasks, particularly in regions responsible for attentional control and executive functions. The research suggests that time perception is a dynamic and flexible process that is influenced by the complex interplay of multiple cognitive and motor systems. Understanding the interactions between cognitive and motor tasks enriches cognitive neuroscience by revealing how multitasking affects mental processes and time perception. These insights have practical applications in human-computer interaction, where user experience can be optimized by considering cognitive load. In clinical psychology, they can inform therapeutic approaches that integrate cognitive and physical rehabilitation strategies. Furthermore, understanding these dynamics can enhance cognitive rehabilitation programs, helping individuals recover from brain injuries or manage conditions that affect cognitive functioning. Future research should focus on further investigating the neural mechanisms that underlie the integration of cognitive and motor processes in time perception, particularly through the use of neuroimaging techniques. Additionally, exploring the effects of emotional states and arousal on time perception may provide a more comprehensive understanding of how humans experience time across different contexts.

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