Revisiting the Temporal Resolution Power (TRP) Hypothesis: An Investigation of the Behavioral and Psychophysiological Aspects of the Relationship Between TRP and Psychometric Intelligence

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Lisa Michaela Makowski
Erlenbach (ZH)

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Abstract

The Temporal Resolution Power (TRP) hypothesis states that individuals who exhibit greater accuracy and sensitivity in temporal information processing tasks also process information faster, coordinate their information processing more effectively, and, therefore, perform better on psychometric intelligence tasks. As an explanation for these individual differences in TRP, it has been suggested that individuals differ in an internal master clock that ticks at a specific rate, which should be reflected in the form of neural oscillations. However, how these neural oscillations can be represented on a psychophysiological level is still unknown. Moreover, as the first part of the TRP hypothesis is merely well established, less is known about its association with the coordination of mental operations. From this perspective, the overall aim of this dissertation was to strengthen and extend the TRP hypothesis at the behavioral and psychophysiological levels. To this end, four studies were conducted in which different aspects of the TRP hypothesis were investigated.

In Study 1 (*N* = 273, *M* = 21.6, *SD* = 2.7), the association between TRP, spatial suppression, as another information processing mechanism, and psychometric intelligence was analyzed on a behavioral level. Study 2 (*N* = 129, *M* = 23.0, *SD* = 3.1) examined to what extent an internal master clock can be reflected on the psychophysiological level by the peak alpha frequency (PAF) measured during resting states, and whether the PAF can mediate the relationship between TRP and psychometric intelligence. Study 3 (*N* = 228, *M* = 22.0, *SD* = 2.9) focused on the second part of the TRP hypothesis by investigating to what extent working memory updating, as a reflection of the coordination of mental operations, mediates the relationship between TRP and psychometric intelligence. In Study 4, a subsample of Study 2 was selected with *N* = 100 (*M* = 22.8, *SD* = 2.9) to investigate how, besides an internal clock mechanism, the involvement of other processing during TRP tasks may be important for understanding the relationship between temporal information processing and psychometric intelligence.

The results showed that the relationship between psychometric intelligence and TRP could be successfully replicated in Studies 1-3. Moreover, in line with the first part of the TRP hypothesis, individuals with higher TRP were also faster in correctly identifying the motion direction of presented visual stimuli (Study 1). Spatial suppression, however, could not make a functional contribution. In line with the second part of the TRP hypothesis, higher TRP also enabled a more effective coordination of mental operations, as indicated by a higher working memory updating, which in turn then also led to higher psychometric intelligence performance (Study 3). Regarding the psychophysiological basis of TRP, although the

frontal/central PAF when measured during resting states with eyes open was positively related to psychometric intelligence, it was not associated with TRP (Study 2). The investigation of neural activity during temporal information processing based on theta and gamma coherence also showed no significant correlation with temporal information processing performance when psychometric differences in intelligence were considered (Study 4). Thus, the individual differences in TRP could neither be explained by the PAF measured at rest nor its relationship to psychometric intelligence by the coherence measures measured during the task.

Based on these four studies, the TRP hypothesis could be further replicated and extended. More specifically, Studies 1 to 3 provided further evidence for TRP as a substantial predictor of psychometric intelligence. Furthermore, the aspects of processing speed and coordination within the TRP hypothesis were confirmed in two new studies. However, it was also shown that spatial suppression was unable to contribute. Besides these behavioral aspects, it was also focused, as the first study to date, on how the internal master clock might be reflected on the psychophysiological level. Even if no clear measure could be found, the analyses offer initial starting points for future studies. This dissertation can, therefore, make an important contribution to the explanation and understanding of the TRP hypothesis and brings us one step closer to understanding why individuals differ in their general intelligence.

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1 Introduction

General intelligence reflects a complex and multifaceted ability. Its existence has been highly debated with the development of several different intelligence structure models (Gottfredson, 1997; Mackintosh, 2011). While much is known about how this ability can be measured, less is known about why individuals differ in it. As an explanation of these differences, cognitive correlates such as the speed of information processing, working memory capacity, and sensory discrimination ability have been investigated. It could be shown that individuals with higher psychometric intelligence process information faster (Doebler & Scheffler, 2016; Jensen, 2006; Mashburn et al., 2023; Schubert & Frischkorn, 2020; Sheppard & Vernon, 2008), actively maintain and process more information in their working memory (Conway et al., 2003; Engle et al., 1999; Heitz et al., 2005; Mashburn et al., 2023), and are better at discriminating perceptual differences (Acton & Schroeder, 2001; Deary, 1994; Helmbold et al., 2006; Jastrzębski et al., 2021; Troche et al., 2014; Troche & Rammsayer, 2009a; Tsukahara et al., 2020). Furthermore, it was demonstrated that a variable derived from various psychophysical timing tasks measuring temporal accuracy and sensitivity could also make a significant contribution to the understanding of psychometric intelligence (Haldemann et al., 2012; Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b). This variable is called temporal resolution power (TRP). It is proposed that its individual differences can be explained by an internal timing mechanism referred to as an internal master clock, which should be reflected in the rate of neural oscillations (Rammsayer & Brandler, 2002, 2007; Surwillo, 1968). In this context, it has been argued that a faster rate of neural oscillation should also be reflected in a higher temporal resolution. This, in turn, should also lead to individuals being able to process their information faster and more effectively. Based on this, the TRP hypothesis was postulated, which states that individuals with a higher TRP also process information faster and coordinate their mental operations more effectively, leading to higher psychometric intelligence scores (Rammsayer & Brandler, 2007). Previous studies have been able to confirm repeatedly this relationship between TRP and psychometric intelligence (Haldemann et al., 2012; Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b). In line with the first aspect of the TRP hypothesis, it was also shown that the association between speed of information processing and psychometric intelligence could be explained in terms of TRP (Helmbold et al., 2007; Pahud et al., 2018). In contrast, the second aspect, which relates to the coordinative aspects of the information processing, has only been investigated once so far (Troche & Rammsayer, 2009b). In this turn, it was shown that higher TRP is associated with a higher working memory capacity, leading to higher performance in psychometric intelligence tests. However, the specific coordination processes have not been studied in detail. It also remains unclear how the internal master clock can be represented on psychophysiological level.

The first aim of the present thesis was to replicate the relationship between TRP and psychometric intelligence in three independent studies. The second aim was to extend previous findings in terms of the TRP hypothesis by examining to what extent spatial suppression (Study 1), as another information processing mechanism, as well as working memory updating, as a reflection of the coordination of mental operations (Study 3), contribute to the understanding of the TRP hypothesis. The third aim focused on examining the psychophysiological basis of the internal master clock underlying TRP. To this end, it was examined to which extent differences in EEG activity during the resting state with the peak alpha frequency (Study 2) and differences in EEG activity during temporal information processing using coherence analyses within the gamma and theta frequency bands (Study 4) can contribute to the understanding of this internal master clock.

The following thesis is structured into five chapters. After the first chapter with an introduction to the topic, the second chapter is focused on the theoretical background and the current state of research. Chapter 3 will cover the study's research questions and the derived hypotheses. In chapter 4, the four different studies are presented as three articles with an additional analysis. Finally, there is a discussion of the research questions and hypotheses in chapter 5, including possible implications and an outlook for future studies.

2 Theoretical Background

Intelligence has fascinated humankind for a long time. Already in the 5th century, before Christ, philosopher Plato and his student Aristotle were trying to define intelligence (Sternberg, 2019). Whereas the former saw intelligence primarily as the ability to learn, the latter focused on reasoning. Since then, many different definitions of intelligence have been developed, of which the one written by Gottfredson (1997) reflects most closely what is understood by intelligence today. Gottfredson (1997) defined intelligence as:

> […] a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings—“catching on”, ”making sense” of things, or “figuring out” what to do. (Gottfredson, 1997, p. 13)

This definition highlights the multi-facet of general intelligence, which was further analyzed by various structure models over the last 125 years (Mackintosh, 2011). The development of these different structure models was also accompanied by an intensive debate on the existence of general intelligence or a *g*-factor. This *g*-factor was first introduced by Spearman (1904) in his two-factor theory of intelligence. Spearman observed that the various measures he implemented in his study, namely academic performance, pitch discrimination, and the tested subjects' musical ability were positively related to each other (Spearman, 1904, 1927). This occurrence of positive associations between different performance measures is also referred to as the positive manifold (Mackintosh, 2011). Spearman then showed that these associations could be explained by a common general factor, which he referred to as *g*. Besides this common factor, each task also has its own specific factor (s), which is unrelated to *g*. Thus, he believed that it was this general factor *g* that all performance measures had in common and that, in turn, could explain the positive associations between the different performance measures.

The view, however, of a common general intelligence factor was not shared by all researchers. Thurstone (1938) believed that general intelligence could not be described by a *g*-factor but by seven primary mental abilities. Also, another researcher named Cattell distinguished general intelligence into two related yet distinct factors: fluid intelligence (ability to solve new problems, recognize rules and reasoning, e.g., matrices test) and crystallized intelligence (knowledge, verbal abilities, e.g., vocabulary knowledge tests; Mackintosh, 2011). In this turn, it was shown that fluid intelligence, also often referred to as *g*F, was highly predictive of *g* and often even indissociable (Blair, 2006).

As a consensus of these models, Carroll (1993) introduced his three-stratum structure model of intelligence which exhibits three levels (stratum). On the lowest level, the different tasks can be found. With these tasks, the originally eight specific abilities (e.g., fluid intelligence, crystallized intelligence, general memory and learning) on the second level (stratum) can be measured. These abilities share common variance, reflected in a general intelligence factor (*g*-factor) at the third stratum and top of the model (Carroll, 1993; McGrew, 2009). The model implements the seven primary mental abilities of Thurstone (second stratum), as well as fluid and crystallized intelligence as in the model proposed by Cattell (second stratum), while also including a general intelligence factor as in Spearman’s model on the first stratum (Mackintosh, 2011; McGrew, 2009). The model was then further revised and renamed to the CHC-model (McGrew, 2009).

Nowadays, the existence of a *g*-factor, general intelligence, is (mostly) accepted

(Mackintosh, 2011). More so, since it has been shown that the *g*-factors assessed by different psychometric intelligence tests were highly related to each other, indicating that *g* is not only a correlational result of specific intelligence measures but an overarching factor found independent from the psychometric measurement (Johnson et al., 2004, 2008). All in all, the existence and measurement of general intelligence have been extensively investigated. However, the why or how general intelligence can be explained remains an open question. Although some of these structure models are named theories (such as Spearman's two-factor theory), they solely describe how general intelligence is structured but do not explain individual differences.

2.1 Intelligence and its Cognitive Correlates

Previous research could show that cognitive correlates can contribute to the understanding of individual differences in psychometric intelligence. Moreover, individual differences in psychometric intelligence were shown to be related to differences in the speed of information processing (Doebler & Scheffler, 2016; Jensen, 2006; Mashburn et al., 2023; Schubert & Frischkorn, 2020; Sheppard & Vernon, 2008), working memory capacity (Conway et al., 2003; Engle et al., 1999; Heitz et al., 2005, 2005; Mashburn et al., 2023), and sensory discrimination ability (Acton & Schroeder, 2001; Deary, 1994; Helmbold et al., 2006; Jastrzębski et al., 2021; Troche et al., 2014; Troche & Rammsayer, 2009a; Tsukahara et al., 2020). The following chapter will describe how and why these cognitive correlates can explain individual differences in psychometric intelligence.

2.1.1 Intelligence and Speed of Information Processing

The speed of information processing (SIP), also referred to as information processing speed or processing speed, describes how fast an individual deals with incoming information (Mashburn et al., 2023). Its individual differences in terms of intelligence have been of interest since Sir Francis Galton aimed to investigate in the 1800s how individual differences in reaction time (RT) tasks and sensory discrimination are related to intelligence. However, due to methodological limitations, he could not show an association between RT and intelligence (Galton, 1883 for review, see Jensen, 2006; Mashburn et al., 2023). It took almost another 100 years to provide the first evidence for a significant negative relationship between RT and psychometric intelligence (Roth, 1964). Since then, it has been repeatedly shown that individuals with higher psychometric intelligence scores process information faster than those with lower psychometric intelligence scores, also known as the mental speed approach (Doebler & Scheffler, 2016; Jensen, 2006; Mashburn et al., 2023; Schubert & Frischkorn, 2020; Sheppard & Vernon, 2008).

At the behavioral level, SIP can be measured with elementary cognitive tasks (ECTs) for which only a few cognitive processes are required. Thus, their performance should not be influenced by prior knowledge or strategies, and for analyzing individual differences in these tasks, the reaction time (RT) and inspection time (IT) are used, not the accuracy measures (Jensen, 1998, 2006). RT refers to the duration an individual needs to respond to a presented stimulus (Jensen, 2006) and can be measured, for example, with tasks as the Hick task (Hick, 1952; for review, see Proctor & Schneider, 2018), the Sternberg task (Sternberg, 1966), the Odd-Man-Out paradigm (Frearson & Eysenck, 1986), and the Posner task (Posner, 1969; Posner et al., 1969). IT describes the minimum time an individual needs to discriminate correctly between two stimuli (Irwin, 1984) which can be visual, tactile, or auditory (Kranzler & Jensen, 1989; Sheppard & Vernon, 2008). Across all these ECT tasks, it was consistently shown that RT, the standard deviation of RT as well as IT regardless of stimulus modality were negatively associated with psychometric intelligence (Doebler & Scheffler, 2016; Grudnik & Kranzler, 2001; Schubert, 2019; Sheppard & Vernon, 2008).

Whereas the existence of the relationship between SIP and psychometric intelligence has been well studied, there is still no consensus on the nature of this relationship (Mashburn et al., 2023). One explanatory approach was introduced by Jensen (1982, 2006) with his oscillation theory. Moreover, he proposed that individuals are faster (mean or median RT) and more consistent (standard deviation of RT) in their SIP based on a higher oscillation rate, i.e., higher frequency of excitatory and refractory phases. This higher oscillation rate is beneficial in information processing since, during the encoding of sensory information, the incoming sensory information can only be held very shortly in sensory memory if it is not transferred to working or long-term memory. In this turn, a faster SIP allows information to be passed on more quickly, enabling an individual with a faster SIP to process more information in the same amount of time as an individual with a slower SIP (Jensen, 1982, 2006). Since working memory (WM) is considered a capacity-limited memory system in which only a limited amount of information can be held temporally during information processing (Baddeley, 1986), a faster SIP also enables faster information processing in WM and a faster transfer into long-term memory or action. This, in turn, also prevents WM from overloading, allowing for a higher response accuracy. As then the demands of WM capacities can be used for more information, this also makes an individual with a higher SIP more efficient. This efficiency is essential for more complex cognitive behavior, e.g., problem-solving (Halford et al., 1998), which might explain the functional relationship between SIP and intelligence (Deary, 2001; Doebler & Scheffler, 2016; Jensen, 2006; Mashburn et al., 2023; Schubert & Frischkorn, 2020; Sheppard & Vernon, 2008), but would also assume an existing relationship between WM capacity (WMC) and psychometric intelligence.

2.1.2 Intelligence and Working Memory Capacity

WM can be defined as “a system or a set of processes, holding mental representations temporally available for use in thought and action” (Oberauer et al., 2018, p. 886). The amount of information this system can actively hold and manipulate is limited, with individuals also differing in this ability called working memory capacity (WMC; Engle et al., 1999; Oberauer et al., 2000; Oberauer et al., 2016; Wilhelm et al., 2013). WMC can be measured using complex span tasks (Daneman & Carpenter, 1980; Turner & Engle, 1989), n-back tasks (Kirchner, 1958), running memory span tasks (Pollack et al., 1959), updating tasks (Miyake et al., 2000) and binding tasks (Wilhelm et al., 2013). Although these WMC tasks differ in their functionality, they are highly related and can be described with a common general WMC factor, indicating that WMC reflects a domain-general construct (Wilhelm et al., 2013). This domain-general WMC has been shown to be strongly linked with general fluid intelligence, with two meta-analyses reporting associations of $r = .72$ (Kane et al., 2005) and $r = .85$ (Oberauer et al., 2005) between WMC and general fluid intelligence. Other studies could also show significant associations of WMC with verbal, fluid, and spatial abilities (Colom & Chun Shih, 2004), with capacity- and speed-related aspects of intelligence (Troche & Rammsayer, 2009b), and with general intelligence (Colom et al., 2005, 2008; Conway et al., 2003). Thus, WMC and general intelligence share a substantial amount of variance, implying the existence of common underlying processes. However, what kind of processes these are, is still an ongoing debate.

There are different theoretical frameworks suggesting that individual differences in short-term memory storage (Colom et al., 2008), temporary bindings (Chuderski, 2019; Oberauer et al., 2008), and executive attention, also referred to as engagement and disengagement theory (Engle, 2018; Engle et al., 1999; Mashburn et al., 2020), explain the relationship between WMC and general (fluid) intelligence. Of these, the binding hypothesis seems particularly important, as it emphasizes that it is not only the pure number of items that an individual can hold, as in the original accounts of short-term memory storage (Colom et al., 2008), but also the number of present relationships between the items, or the relationship between their context, that can explain the link between WMC and general fluid intelligence (Oberauer, 2005, 2019; Oberauer et al., 2007, 2008). The quality but also number of these temporary bindings differ between individuals (Oberauer et al., 2008). However, since the same bindings will not always be needed, it is also important to be able to break certain relations, i.e., unbinding, and build new ones in order to ensure efficient information processing. So, in addition to WMC, which reflects how many of these bindings can be activated at once, there is another process called WM updating, which comes into play when new relevant bindings replace older and no longer relevant ones (Oberauer, 2005, 2019; Oberauer et al., 2007, 2008). Since WMC reflects the space that defines how much information can be processed and maintained in parallel, WM updating helps the system process this information more efficiently (Chuderski, 2019; Oberauer, 2009, 2019). These are also relevant processes when solving, for example, a matrices test since new rules need to be recognized, retained, and discarded in the presence of other rules (Chuderski, 2019; Oberauer et al., 2007). Empirically, this theory showed strong support (Oberauer, 2005; Schubert et al., 2023; Wilhelm et al., 2013).

Since WMC is limited in its capacity and time to maintain information actively, it seems important that information is processed as quickly as possible. As described in the chapter before with Jensen's oscillation theory (1982, 2006), it is, therefore not only the SIP that is important when it comes to understanding why people differ in their psychometric intelligence. Instead, it is also the amount of information that can be actively maintained in a short period of time. Moreover, as information processing is not a static process, these bindings need to be constantly refreshed and updated, indicating the importance of WMC and WM updating (Chuderski, 2019; Oberauer et al., 2007). However, to actively maintain information and establish and update bindings, not only the processing speed but also the resolution of sensory perception and processing are important (Mashburn et al., 2023). In this sense, differences in sensory processing could provide further insights into why individuals differ in their intelligence.

2.1.3 Intelligence and Sensory Discrimination Ability

How precisely an individual can process and judge perceptual differences of auditory, visual, and tactile stimuli can be measured with sensory discrimination ability measures (Burgoyne et al., 2020). Already early on, Galton (1883) proposed that differences in this ability might explain why individuals differ in their intelligence. Also, Spearman (1904) was intrigued by this idea and investigated how sensory discrimination in pitch, weight, and color might be related to general intelligence and revealed moderate to high positive associations on the manifest level. Since then many other studies have replicated this positive association with general intelligence using discrimination tasks in which the pitch (Jastrzębski et al., 2021; Troche & Rammsayer, 2009a), duration (Jastrzębski et al., 2021; Troche et al., 2014; Troche & Rammsayer, 2009a; Tsukahara et al., 2020) and loudness (e.g., Deary et al., 2004; Troche

& Rammsayer, 2009a) in the auditory modality, brightness (e.g., Troche & Rammsayer, 2009a), duration (Jastrzębski et al., 2021; Troche et al., 2014), line (e.g., Troche et al., 2014; Tsukahara et al., 2020), circle (e.g., Tsukahara et al., 2020) and color (Acton & Schroeder, 2001) in the visual domain, and pressure (Li et al., 1998), texture (Li et al., 1998; Roberts et al., 1997) and shape (Roberts et al., 1997; Stankov et al., 2001) in the tactile modality had to be discriminated. Despite these modality differences, already early on, Spearman (1904) derived a common general discrimination factor from different sensory discrimination measures that was almost perfectly related to *g* (Spearman, 1904). This indicated that these different sensory tasks shared common underlying processes that, in turn, were highly associated with general intelligence. These findings were further replicated by other studies showing a positive association between general intelligence and a general discrimination ability factor derived from discrimination tasks of different modalities (Jastrzębski et al., 2021; Troche et al., 2014; Troche & Rammsayer, 2009a; Tsukahara et al., 2020). In this turn, it was also shown that although sensory discrimination ability and general intelligence are highly related, they are still dissociable constructs (Jastrzębski et al., 2021; Troche et al., 2014; Troche & Rammsayer, 2009a).

As an explanation for this close relationship between psychometric intelligence and general sensory discrimination ability, previous studies suggested a mediating role of WMC, as WM processes are required for task processing of both constructs (Jastrzębski et al., 2021; Troche et al., 2014; Voelke et al., 2014). In line with this, previous studies showed that WMC could completely explain the relationship between general sensory discrimination ability and psychometric intelligence (Jastrzębski et al., 2021; Troche et al., 2014). Although WM processes are required in sensory discrimination tasks, a recent study argues that it is the intensity of attention directed to task-relevant information, an aspect of attention control, which should explain the link between general sensory discrimination ability and general intelligence and between sensory discrimination ability and WMC (Tsukahara et al., 2020). The authors confirmed their notion in two independent studies showing that attention control fully mediated both relationships.

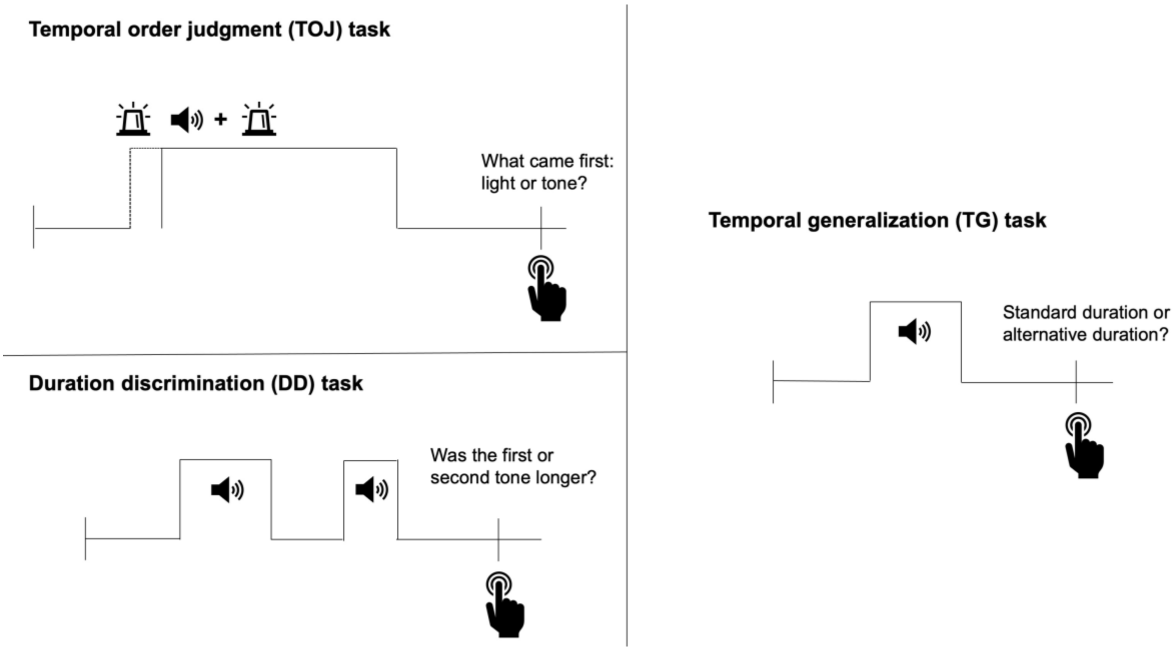
Overall, many studies have shown what Galton already believed that there is a general sensory discrimination ability across modalities, which is highly associated with general intelligence. In contrast to the assumptions of Galton and Spearman, however, these are still dissociable constructs (Jastrzębski et al., 2021; Troche et al., 2014; Troche & Rammsayer, 2009a). Although these discrimination tasks differ in their modality, they have one perceptual feature in common: the presented duration of a stimulus. In terms of an association with psychometric intelligence, it was shown that temporal and non-temporal discrimination could be dissociable from each other, regarding the manifest (Helmbold et al., 2006) but also the latent level (Jastrzębski et al., 2021; Troche et al., 2014; Troche & Rammsayer, 2009a). Although duration discrimination is a part of sensory discrimination ability, a general factor derived from temporal discrimination tasks could independently explain variance in psychometric intelligence (Rammsayer & Brandler, 2007), suggesting an important role of temporal information processing.

2.2 Intelligence and Temporal Resolution Power (TRP)

Temporal information processing measures how accurately humans perceive and process temporal information (Grondin, 2001, 2010). When it focuses on durations in the subsecond (below one second) to second (above one second) range, it marks an important process involved in cognitive processing, for example, in memory, perception, or motor activity processes (Matthews & Meck, 2016). It can be assessed by tasks focusing on interval timing, rhythms, implicit timing, and event timing that mostly implement visual and/or auditory stimuli (van Wassenhove et al., 2019). In terms of interval timing tasks, it is also possible to differentiate into prospective, i.e., participants are informed that they need to focus on temporal information before the task, and retrospective timing tasks, i.e., participants are not informed before the task that they need to focus on temporal information, but get asked about it after (Grondin, 2010). Out of these, prospective interval timing, rhythms, and event timing tasks were implemented to investigate possible associations with general intelligence. Examples of prospective interval timing and event timing tasks are presented in Figure 1. In this turn, it should be noted that event-timing tasks are solely presented in the subsecond range (Fraisse, 1984; van Wassenhove et al., 2019). Rhythm perception and interval timing tasks such as the duration discrimination or temporal generalization task can be presented in the second or subsecond range (Grondin, 2010; Matthews & Meck, 2016; van Wassenhove et al., 2019).

Figure 1

An illustration of the different temporal information processing tasks used in the investigation of individual differences in psychometric intelligence



Although temporal information processing tasks can be differentiated into these different categories and implemented durations (subsecond to second range), already early on, it was believed, especially for interval timing tasks, that they share a common underlying process. Moreover, with the so-called pacemaker-accumulator models, the existence of an internal clock responsible for individual differences in timing accuracy in these tasks was proposed (Grondin, 2001, 2010; van Wassenhove et al., 2019). According to these models, each individual has an internal pacemaker or clock that emits pulses at a particular frequency. These pulses are then counted by an accumulator for the duration of the presented interval, as, for example, for a 1000 ms tone (Creelman, 1962; Grondin, 2001, 2010; Treisman, 1963). The resulting number should then reflect the perceived length of the presented 1000 ms tone, thus, how accurately a temporal interval was encoded. This indicates that individuals with a pacemaker emitting more pulses might be able to sample the presented duration more accurately than those with fewer pulses. It was further suggested that these pulses are reflected by neural oscillations (Grondin, 2010; Treisman, 1963; Treisman et al., 1990, 1994).

In further developments of these models, the role of memory and decision processes (Scalar Timing, Scalar Expectancy Theory; Gibbon et al., 1984), as well as attentional processes (Attentional Gate Model; Block & Zakay, 1997), were implemented. However, it should be noted that there are also opposing views suggesting distinct timing mechanisms depending on stimulus duration and type. Moreover, with the use of dual-task paradigms (e.g., performing a working memory task in parallel to a DD task), it was shown that in the processing of longer intervals (> 500 ms as in Michon, 1985; Rammsayer & Lima, 1991; > 250 ms in Buonomano et al., 2009; Spencer et al., 2009) cognitive processes such as working memory or attention are involved (e.g., Brown, 1997; Mioni et al., 2020, 2021; Rammsayer & Lima, 1991; Zakay, 1993), whereas short or brief duration were believed to be relatively independent of these cognitive processes (Ivry & Spencer, 2004; Lewis & Miall, 2003; Rammsayer & Lima, 1991). In terms of stimulus type, it was shown that in very short intervals in the subsecond range, participants showed higher performance in DD tasks with filled (e.g., tone) than with empty intervals (e.g., onset and offset is marked by noise burst, in between these bursts is silence; Grondin, 2001; Rammsayer, 2014).

2.2.1 TRP Hypothesis and its Background

Similarly to these models of a common timing mechanism, although from a different background, Surwillo (1968) also proposed the existence of an internal clock, which he referred to as a master clock. According to him, this master clock can be viewed as a property of the central nervous system that should explain individual differences in information processing by being responsible for the coordination of different neural activities. Therefore, having a faster clock rate, i.e., a faster neural oscillation rate, should enable one to process information faster and more accurately (Surwillo, 1968). Thus, in line with Jensen’s oscillation theory (1982, 2006), Surwillo (1968) also assumed the importance of neural efficiency in information processing. In contrast to Jensen (1982, 2006), however, Surwillo (1968) emphasized the role of an internal master clock for information processing speed. Also, Surwillo (1968) did not use his notion to explain intelligence differences but to explain age-dependent differences in information processing. It was then Rammsayer and Brandler (2002) who developed his theory further in explaining individual differences in general intelligence (for an illustration, please see Figure 1 in Article 2). To further illustrate their idea, one could imagine two individuals, A and B, with individual B showing half the clock speed or rate as individual A. This indicates that individual B also only processes half of the information than individual A and will also make more mistakes than individual A. Thus, individual B will be less efficient in information processing and make more mistakes in ECTs and psychometric intelligence tests (Rammsayer & Brandler, 2002).

Whereas Burle and Bonnet (1997, 1999) could provide the first evidence of an internal clock mechanism being associated with RT tasks, they did not investigate direct measures of such an internal clock in the form of temporal information processing tasks or intelligence measures. However, in turn, for the notion by Rammsayer and Brandler (2002) to be true, it should be first shown that tasks reflecting clock speed as different temporal information processing tasks can reflect such an internal master clock. Second, they should be related to general intelligence. Proceeding from this idea, it was demonstrated that different interval, event timing, and rhythm perception tasks were closely related (Rammsayer & Brandler, 2002, 2004). Moreover, with the use of exploratory and principal factor analysis, it was possible to derive a common factor, termed temporal resolution power (TRP; Rammsayer & Brandler, 2004, 2007). This TRP factor was then shown to be highly associated with general intelligence, which led to the proposition and further investigation of the TRP hypothesis (Rammsayer & Brandler, 2002, 2007).

According to the TRP hypothesis, individuals with higher TRP also process information faster and are more effective at coordinating their mental operations (Rammsayer & Brandler, 2002, 2007). This, in turn, leads then to higher psychometric intelligence scores. In the past 20 years, this hypothesis has been replicated various times (Haldemann et al., 2012; Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b). Moreover, it was shown that TRP could explain between 22 % (Haldemann et al., 2012) and 44 % (Helmbold et al., 2007) of variance in psychometric intelligence measures, indicating it to be a substantial predictor of psychometric intelligence. Whereas most studies implemented auditory temporal information processing tasks, it was also shown that TRP could be derived from visual timing tasks as well as from visual and auditory timing tasks (Haldemann et al., 2011, 2012). In both cases, substantial, albeit a bit smaller, associations with psychometric intelligence could be found.

2.2.2 TRP and Speed of Information Processing

Besides the investigation of TRP and psychometric intelligence, Rammsayer and Brandler (2007) also implemented a modified Hick task and derived a factor from the Hick parameters. This Hick factor was also significantly associated with general intelligence (Rammsayer & Brandler, 2007). When both the TRP and Hick factor were entered into a regression model, the factor derived from the temporal information processing tasks could explain significantly more variance in general intelligence than the factor reflecting SIP. Thus, TRP seemed to be a more important predictor of psychometric intelligence than SIP. These found association between TRP, SIP, psychometric intelligence were then further investigated by Helmbold et al. (2007) using structural equation modeling (SEM). As in previous studies (Helmbold & Rammsayer, 2006; Rammsayer & Brandler, 2007), a positive relationship between TRP and psychometric intelligence could be shown. They could also provide evidence that TRP and SIP are related yet dissociable constructs. With a mediation analysis, they then further showed that TRP was more important in explaining differences in general intelligence and accounted for the association between SIP and general intelligence (Helmbold et al., 2007). However, since in all these studies, SIP was only measured using one kind of task, namely the Hick paradigm, it remained unclear to what extent this might have had an impact on the results.

In another study, Pahud et al. (2018) tried to corroborate these findings by investigating the common relationships between TRP, SIP, and psychometric intelligence using an equivalent number of tasks per TRP and SIP variable. They implemented three TRP measures (TOJ, DD, TG) in the subsecond range as well as three SIP measures (Hick paradigm, Posner task, continuous performance task). By means of a latent variable approach named fixed-links modeling, an increasing latent variable and a constant latent variable from each SIP measure were derived, which were further reduced to a higher-order latent increasing (dependent on task demands) and a higher-order latent constant variable (independent on task demands) (Pahud et al., 2018). Their results then showed a substantial link between TRP and general intelligence, with TRP explaining 36% of the variance in general intelligence. Moreover, they could show that TRP was also associated with SIP, as well as SIP being associated with general intelligence. By means of a mediation analysis, they found that TRP completely mediated the relationship between the higher-order constant latent variable (SIP independent of task demands) and general intelligence. This finding was interpreted as a replication of Helmbold et al. (2007), indicating that TRP is more indicative of individual differences in general intelligence than SIP. When SIP was placed as a mediator between TRP and psychometric intelligence, their relationship remained unaffected.

Thus, as stated in the first part of the TRP hypothesis, it was repeatedly shown that individuals with higher TRP, also show a faster information processing, which in turn then enables a higher performance in psychometric intelligence tests (Helmbold et al., 2007; Pahud et al., 2018). This faster processing, however, should also lead to lower error rates which would be in line with the oscillation theory by Jensen (1982, 2006), as described in *2.1.1*. As stated in the second part of the TRP hypothesis, these additional processes might be reflected by the coordination of mental operations.

2.2.3 TRP and Coordination of Mental Operations

The second notion of the TRP hypothesis can be interpreted in terms of the association between WMC and psychometric intelligence (Conway et al., 2003; Engle et al., 1999; Heitz et al., 2005; Mashburn et al., 2023). In this context, it was argued that the coordination of information processing becomes particularly important when only a certain amount of resources is available, as is the case with WMC. On this basis, it was proposed that higher TRP would consequently facilitate the coordination of information processing, which in turn should enable a higher WMC. This notion, however, was only once investigated by Troche and Rammsayer (2009b) who investigated the possible interplay between TRP, WMC, and psychometric intelligence using SEM. Their results revealed high associations between TRP, WMC, and psychometric intelligence. Using a mediation analysis, they further revealed that WMC fully mediated the relationship between TRP and psychometric intelligence. This indicated that individuals with higher TRP, also coordinated their mental operations better, which in turn allowed for a higher WMC, leading then to higher psychometric intelligence scores. Thus, their study could provide the first evidence of a possible relationship between TRP, WMC, and psychometric intelligence (Troche & Rammsayer, 2009b). However, they also noted certain limitations as they found a very high association ($r = .88$, $r = .85$) between WMC and the implemented reasoning and capacity intelligence measures as derived from the Berliner Intelligence Structure Test. They explained this with the broad assessment of WMC with three different tasks (numerical memory-updating, figural dot span, verbal monitoring). Since the study by Troche and Rammsayer (2009b) is the first and only study to investigate the role of the coordination aspect of the TRP hypothesis, further studies are needed to expand the evidence.

2.3 How to Substantiate the TRP Hypothesis?

As described before, TRP represents a substantial predictor of psychometric intelligence (Haldemann et al., 2012; Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b). Previous studies have focused on providing evidence in terms of its association with SIP (Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007) but also WMC (Troche & Rammsayer, 2009b). In this context, however, it could also be interesting to investigate how other information processing mechanisms can contribute to the understanding of TRP and its relationship with psychometric intelligence. Furthermore, it is still unknown which psychophysiological measurable neural oscillations can explain individual differences in the internal master clock and thus also in TRP. The following section outlines which information processing mechanisms and which psychophysiological could contribute to a further understanding.

2.3.1 TRP and Spatial Suppression as Competing Bottom-up Approaches to Intelligence

Another information processing mechanism closely linked with psychometric intelligence is spatial suppression (Arranz-Paraíso & Serrano-Pedraza, 2018; Cook et al., 2016; Melnick et al., 2013; but also see Linares et al., 2020; Troche et al., 2018). Although this mechanism can occur in different sensory modalities, it has so far only been associated with psychometric intelligence on the visual level (Ankri et al., 2020; Tadin et al., 2011). Therefore, the following descriptions will also be focused on spatial suppression in visual processing.

Spatial suppression manifests itself within visual processing when we perceive the motion of a stimulus. If the stimulus is relatively small, it can be easily distinguished from the background, making it possible to detect its correct motion direction (e.g., right or left) quickly (Tadin, 2015; Tadin et al., 2003). However, the larger the stimulus becomes, the more difficult it is to distinguish it from the background and, thus, to perceive the correct motion direction. This difficulty in correctly identifying the motion direction with increasing stimulus size is referred to as spatial suppression and can be assessed with visual psychophysical tasks (Tadin, 2015; Tadin et al., 2003). In these tasks, the presentation time of the next stimulus becomes shorter in case of a correct response and longer in case of an incorrect one. The resulting presentation times are then gathered as a threshold per stimulus size that reflects the presentation time an individual needed to accurately detect the motion direction of the presented stimulus, usually in 83% of the trials (Tadin et al., 2003). Since this increase in threshold time for the larger stimulus should indicate spatial suppression, a difference value is used to measure spatial suppression in which the logarithmized threshold of the smallest stimulus is subtracted from that of the largest stimulus (Tadin et al., 2003). A high spatial suppression index would indicate then that individuals were quick in identifying the motion direction correctly in a small stimulus but had difficulties doing so in a large stimulus. This might imply a possible influence of processing speed in recognizing the motion direction of small stimuli. However, difficulties arise with larger stimuli, which is reflected in longer presentation times and might indicate the need for ongoing perceptual suppression processes (Melnick et al., 2013; Tadin, 2015; Tadin et al., 2003).

On the neural level, spatial suppression is linked to the center-surround mechanisms associated with suppression in the cortical medial temporal area (Lin & Tadin, 2019; Liu et al., 2016; Tadin, 2015; Tadin et al., 2003, 2011; Tadin & Lappin, 2005). Whereas in normal visual processing, brighter or bigger stimuli are considered to be easier perceived, this cannot be so easily transferred to the perception of motion (Liu et al., 2016; Tadin, 2015). Moreover, in motion perception, large and high-contrasted stimuli expand over the center of a receptive field into the surround area. This is also referred to as center-surround antagonism and leads to neural suppression since the response of a neuron gets inhibited (Lin & Tadin, 2019; Liu et al., 2016; Tadin, 2015; Tadin & Lappin, 2005). As such a suppression process should facilitate information processing, it might be also important for psychometric intelligence (Burgess et al., 2011; Dempster, 1991; Gray et al., 2003). Thus, it was suggested that the thresholds of the smaller stimulus sizes should be negatively associated with psychometric intelligence since they are associated with motion processing speed (Melnick et al., 2013). However, the larger the stimulus gets, the harder it is to perceive the correct motion direction, which results in a neural surround suppression. Thus, the relationship between psychometric intelligence and the thresholds should be reversed for larger stimuli. This would indicate that a large spatial suppression index would be positively associated with psychometric intelligence. This, in turn, was shown by the study of Melnick et al. (2013), which revealed a high and significantly positive association between psychometric intelligence and the spatial suppression index (in their study 1: $r = .64$, in their study 2: $r = .71$). Thus, individuals with higher psychometric intelligence showed lower thresholds during the smallest stimulus size but higher ones during the largest one (Melnick et al., 2013). For individuals with lower intelligence, the thresholds were comparable over the different stimulus sizes, i.e., showing small spatial suppression indices. This finding was further replicated by two other studies (Arranz-Paraíso & Serrano-Pedraza, 2018; Cook et al., 2016 but also see Linares et al., 2020; Troche et al., 2018).

Thus, spatial suppression, as TRP, also contributes to the understanding of individual differences in psychometric intelligence. When comparing these two mechanisms, it is noticeable that both can be interpreted as bottom-up mechanisms that facilitate efficient information processing which in turn is important for psychometric intelligence (Arranz-Paraíso & Serrano-Pedraza, 2018; Cook et al., 2016; Haldemann et al., 2012; Helmbold et al., 2007; Melnick et al., 2013; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b). Both also involve temporal information processing. Whereas TRP is a direct measure of temporal accuracy and sensitivity but is also associated with SIP (Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007), processing speed seems to be also involved in the thresholds of the motion perception of at least the small stimuli in a spatial suppression task (Melnick et al., 2013). Besides these similarities, however, they also differ in other parts, as spatial suppression in its association with psychometric intelligence is limited to the visual modality, and TRP is associated with psychometric intelligence over different modalities (Haldemann et al., 2011, 2012). Also, although faster SIP might influence the perception of smaller stimuli, it might not be so influential on larger stimuli and therefore, also not be reflected within the spatial suppression index. From the perspective that spatial suppression was shown to be important in terms of information processing, it might also be important to investigate how TRP and spatial suppression are related to each other as well as how spatial suppression can be integrated in the relationship between TRP and psychometric intelligence.

2.3.2 Psychophysiological Basis of the Relation Between TRP and Intelligence

Based on the theory of Jensen (1982, 2006) as well as the expanded notion of an internal master clock by Surwillo (1968) and Rammsayer and Brandler (2002, 2007), it was put forward that the speed of neural oscillations can explain why a faster information processing, as in Jensen (1982, 2006), and a higher TRP, as in Rammsayer and Brandler (2002, 2007), is associated with higher psychometric intelligence. However, neither Jensen (1982, 2006) nor Rammsayer and Brandler (2002, 2007) specified how these neural oscillations can be represented.

Neural oscillations can be measured with a psychophysiological and noninvasive method named electroencephalography (EEG), for which a certain number of electrodes (usually varying between 32 to 256 electrodes) are positioned on the scalp (Cohen, 2014). The oscillations measured with these electrodes can be described by their frequency, power, and phase. The frequency of an oscillation (in Hz) reflects the number of cycles per second, i.e., the speed of the oscillation. In contrast, the phase refers to when the oscillation occurs, i.e., the timing (Cohen, 2014). The power can be derived through frequency analysis, e.g., Fast Fourier Transformation (FFT), and is calculated as the squared amplitude of the signal in a frequency band, describing the strength of a particular frequency band (Cohen, 2014). In this regard, most studies distinguish between the following five frequency bands: delta (0.5-4 Hz), theta (4-7 Hz), alpha (7-13 Hz), beta (13-30 Hz), and gamma (> 30 Hz) (Buzsáki, 2006; Cohen, 2014; Klimesch et al., 1993). Previous studies have shown that the five frequency bands are associated with different cognitive processes (Başar et al., 1999; Cohen, 2014; O. Jensen & Mazaheri, 2010; Klimesch, 2012). However, it should be also noted that the frequency range (in Hz) of these frequency bands can vary between studies (Cohen, 2014).

One way to measure the involvement of these different frequency bands is during a so-called resting state during which participants, for example, have to close their eyes for 60 s or keep their eyes open for 60 s. Another possibility is to measure them during a task and focus on task-related activity (Cohen, 2014). In this turn, it is also important to differentiate between studies implementing an individual approach and those implementing a task approach (Basten et al., 2015; Basten & Fiebach, 2021). In a task approach, the task-specific brain activations are examined without considering individual differences. On the other hand, an individual approach focuses on the activations that can explain why individuals differ in their performances.

2.3.2.1 Peak Alpha Frequency as an Internal Master Clock. As indicated by the theoretical frameworks of Jensen (1982, 2006) as well as Rammsayer and Brandler (2002, 2007), it seems to be the speed of an oscillation that is important for individual differences in psychometric intelligence and also to explain differences in TRP that in turn are linked to psychometric intelligence. This speed of an oscillation should be reclected by the rate of neural oscillations, thus, the number of cycles per second as indicated by Hz. When looking closer at the power spectrum of the alpha frequency band measured at rest, there is indeed a prominent peak in the alpha frequency band in which subjects have been shown to differ substantially (Angelakis, Lubar, Stathopoulou, et al., 2004; Drewes et al., 2022; Hilger et al., 2022). This peak is referred to as peak alpha frequency (PAF) and reflects the point with the highest power within the alpha frequency spectrum (in Hz). It has been interpreted as a measure of "cognitive preparedness" (Angelakis, Lubar, Stathopoulou, et al., 2004, p. 896), processing speed (Jann et al., 2010; Klimesch et al., 1996; Ociepka et al., 2022), and resolution of information processing (Mierau et al., 2017; Samaha & Romei, 2023). These definitions have one thing in common, as they all indicate that PAF is involved in information processing. Furthermore, the PAF has been shown to reflect a stable measure, showing high heritability (Posthuma et al., 2001) and retest-reliability when measured during resting state (Popov et al., 2023). Based on this, PAF was proposed to be a good candidate for assessing psychometric intelligence differences. In line with this idea, previous studies revealed a positive relation between psychometric intelligence and PAF (Angelakis, Lubar, & Stathopoulou, 2004; Anokhin & Vogel, 1996; Leno et al., 2021; Doppelmayr et al., 2002; Grandy et al., 2013). However, there were also studies unable to show an association with psychometric intelligence (Finnigan & Robertson, 2011; Ociepka et al., 2022; Pahor & Jaušovec, 2016; Posthuma et al., 2001; Trammell et al., 2017). Based on these findings, it could not be systematically shown that individuals with higher psychometric intelligence also show a higher PAF in the resting state.

For PAF to reflect a possible psychophysiological master clock underlying TRP, it also needs to be shown how PAF is related to TRP. As no previous study has investigated this, only the results of studies focused on using single temporal information processing tasks can be reported. In this turn, it was demonstrated that PAF was positively associated with the performance in an event-timing task in the subsecond range (Samaha & Postle, 2015). However, in two other studies also using durations in the subsecond range, there was no significant association between the PAF and the timing performance (Milton & Pleydell-Pearce, 2017; Venskus & Hughes, 2021). In another study by Glicksohn et al. (2009), there was also, at first, no association between PAF measured during a resting state and the performance in a temporal production task. However, when the PAF was differentiated by hemisphere (right versus left), and both were included as predictors of task performance, both sides contributed to the understanding of individual differences in the task. However, overall, as seen before, also in terms of temporal information processing, the previous findings appear inconsistent.

Possible reasons for these inconsistencies in terms of PAF and psychometric intelligence, as PAF and temporal information processing, may lie in the methodological differences between these studies. Moreover, the presented studies differed in the resting state, during which they measured PAF, the number of resting states used, and the electrodes at which PAF was measured. In terms of resting states, some studies measured PAF only during a resting state with eyes closed (Anokhin & Vogel, 1996; Finnigan & Robertson, 2011; Glicksohn et al., 2009; Pahor & Jaušovec, 2016; Posthuma et al., 2001; Samaha & Postle, 2015) or eyes open (Leno et al., 2021; Ociepka et al., 2022). Even others derived a difference score between eyes open and closed (Trammell et al., 2017). Only a few studies investigated both resting states separately (Angelakis, Lubar, & Stathopoulou, 2004; Angelakis, Lubar, Stathopoulou, et al., 2004; Grandy et al., 2013). This, however, might be important since previous studies indicate functional differences in resting states with eyes open compared to eyes closed (Anderson & Perone, 2023; Barry et al., 2007). More specifically, an eyes open resting state condition is proposed to reflect a measurement of baseline activation, and the eyes closed condition to measure the baseline of arousal (Anderson & Perone, 2018, 2023; Barry et al., 2007).

Regarding the used electrode sites, PAF was primarily measured at parietal and occipital electrodes (Glicksohn et al., 2009; Grandy et al., 2013; Milton & Pleydell-Pearce, 2017; Posthuma et al., 2001; Samaha & Postle, 2015; Trammell et al., 2017; Venskus & Hughes, 2021). In turn, other studies used all electrodes by averaging them into one PAF score (Angelakis, Lubar, & Stathopoulou, 2004) or focused on occipital electrodes for some and frontal electrodes for other participants (Ociepka et al., 2022). There are, however, also some studies that differentiated their electrode sites, for example, in frontal and parietal electrodes (Anokhin & Vogel, 1996; Doppelmayr et al., 2002; Finnigan & Robertson, 2011; Pahor & Jaušovec, 2016). As the electrode sites could contribute to the specific understanding in terms of cognitive processes, it might be important to focus on all electrodes separately or systematically investigate how these electrodes can be summarized.

Besides the implemented resting states and electrode sites, in most of these previous studies, the PAF was mainly measured once, with only a few studies combining several measurement points (Angelakis, Lubar, & Stathopoulou, 2004; Angelakis, Lubar, Stathopoulou, et al., 2004; Grandy et al., 2013). However, this seems necessary, as it has been shown that the PAF can be affected by state differences (Angelakis, Lubar, & Stathopoulou, 2004; Angelakis, Lubar, Stathopoulou, et al., 2004; Haegens et al., 2014; Mierau et al., 2017). These methodological differences complicate the comparison of previous studies. Nevertheless, it might still be that the PAF could contribute to the psychophysiological understanding of the internal master clock and, thus, to understanding TRP and its relationship with psychometric intelligence.

2.3.2.2 Gamma and Theta Coherence. It has been shown that most cognitive processes are not only associated with activity in a specific area of the brain but can be attributed to the involvement of diverse and dynamic activity patterns within the brain (Bowyer, 2016; Decker et al., 2017). Thus, besides focusing on the power or frequency at certain electrodes within a frequency band, more and more studies also focus on the synchronization (communication) between electrodes during resting state or task processing as measured with a coherence analysis (Fries, 2005, 2015). This analysis provides information about the synchronization between different electrodes with high temporal resolution by being able to possibly identify activations patterns that might be linked to cognitive processes (Bowyer, 2016; Cao et al., 2022; Cohen, 2014). To this end, coherence can be analyzed phase- or power-based within one frequency band or across different frequency bands, and these analyses can be based on the sensor space (electrodes) or source space (linking activity to brain regions; Cohen, 2014). One measure often used to quantify coherence in the sensor space is the magnitude-squared coherence, in which the phase information is weighted by the magnitude information within a specific frequency band. Thus, this measure shows how similar two signals within a frequency band are, for example, the activity in F5 and P3 (Malekpour et al., 2018). The resulting coherence value varies between 0 and 1. A value of 0 indicates that the two signals are not linearly dependent, and a value of 1 shows a high relation between the two signals. As magnitude-squared coherence reflects a symmetric measure, the coherence value between F3-P5 is equivalent to the one between P5-F3 (Cohen, 2014; Malekpour et al., 2018). Thus, magnitude-squared coherence can help identify if two brain regions exhibit similar activity patterns, which might also be important to understanding individual differences.

According to the TRP hypothesis, the relationship between TRP and psychometric intelligence should be based on a sensory process, namely the rate of an internal master clock. This would indicate that TRP and psychometric intelligence should be associated based on differences in sensory processing. In order to investigate possible differences in sensory processing on the psychophysiological level, previous studies focused on gamma coherence (Karakaş et al., 2001; Strüber & Herrmann, 2022; von Stein & Sarntheim, 2000). However, as the gamma coherence differed in these studies based on between which electrode sites it was measured, it remains unknown to what extent modality-specific areas or modality-independent sensory areas were activated. Moreover, it should also be noted that other studies interpret the gamma coherence as a potential top-down mechanism, which will be again taken on in the discussion (Bonnefond & Jensen, 2015; Leicht et al., 2021).

In terms of psychometric intelligence, it was shown that individuals with higher intelligence showed increased gamma coherence (25-60 Hz) during resting state with eyes closed over the whole scalp (Lee et al., 2012) and increased gamma coherence (31-49 Hz) between occipital and parietal electrodes when measured during a cognitive task that was related to psychometric intelligence (Jaušovec & Jaušovec, 2005) compared to individuals with lower psychometric intelligence. These findings overall show a positive association between gamma coherence and psychometric intelligence. However, as both findings differ in their electrode selection and timepoint of testing (eyes closed versus during the task), it remains unclear to what extent the increased gamma coherence reflected the same general sensory process in both studies.

Regarding temporal information processing, to date, there has only been one study that investigated gamma coherence during temporal information processing (Hoodgar et al., 2022). The authors could show gamma coherence between left-sided temporal and central and between right-sided frontal and temporoparietal electrode sites during the encoding of a shorter interval (500 ms) and gamma coherence between frontal and central, right frontal and left temporal, left-sided frontal, and between left-sided frontal and parietal electrode sites during the encoding of a longer interval (1 s). However, as this study was limited to a task approach, no statements can be made about how gamma coherence could explain individual differences in temporal information processing.

In contrast to the notion that the association between TRP and psychometric intelligence is attributable to differences in sensory acuity, previous studies showed that the relationship between TRP or, in general, sensory discrimination ability and psychometric intelligence could be explained by common WMC involvement (Jastrzębski et al., 2021;

Troche et al., 2014). This involvement of WMC is reflected in sensory discrimination tasks as follows: during the task, the perceptual features of one stimulus (e.g., the brightness) need to be encoded and actively retained, while the features of a second stimulus are simultaneously encoded and then both are compared to each other. In this sense, it has been shown that individuals with a higher WMC perform better in these discrimination tasks (Jastrzębski et al., 2021; Troche et al., 2014; Tsukahara et al., 2020). Also, for performance in interval timing tasks which are used to derive TRP, previous studies have highlighted the role of working memory (e.g., Brown, 1997; Mioni et al., 2020, 2021; Rammsayer & Lima, 1991; Zakay, 1993). However, in order to encode but also retain and compare the duration of the presented stimuli, sufficient attention must be also focused on the task (Tsukahara et al., 2020). At the same time, irrelevant information or distractions must be ignored. This process, known as attention control, is a top-down process needed to organize and modulate information processing to behave goal-oriented (Burgoyne et al., 2023; Kane & Engle, 2003; Mashburn et al., 2020). It has been shown to be highly associated with psychometric intelligence and able to explain the relation between WMC and psychometric intelligence (Burgoyne et al., 2020; Heitz et al., 2005; Kovacs & Conway, 2016; Mashburn et al., 2020). In this turn, a recent study could provide evidence for a complete mediation of the relation between sensory discrimination ability and WMC, as well as sensory discrimination ability and psychometric intelligence by attention control (Tsukahara et al., 2020). Regarding TRP, it is unknown how this top-down process might be involved in the relationship to psychometric intelligence. However, from studies focusing on single temporal information processing tasks as well as the pacemaker-accumulator models (Brown, 2008; Grondin, 2010; Matthews & Meck, 2016; Zakay & Block, 1996), it has been argued that top-down processes such as attention control might explain differences in temporal information processing (Bausenhart et al., 2016; Broadway & Engle, 2011; Ciria et al., 2019; Dyjas et al., 2012; Ogden, 2014; van Rijn, 2016).

In order to show these individual differences in task processing on the psychophysiological level, previous studies showed that individual differences in attention control can be reflected by differences in theta coherence between frontal (but also frontocentral) and posterior electrodes (occipital, parietal) when measured during tasks involving attention control (Basharpoor et al., 2021; Eschmann et al., 2020; Karakaş, 2020; Myers et al., 2021; Nurislamova et al., 2019; Sauseng et al., 2005, 2006, 2007; von Stein & Sarntheim, 2000). In this context, it was shown that a higher amount of attention control was associated with an increased theta coherence between these frontal and posterior electrode sites.

In line with previously reported behavioral reports, it could be demonstrated that psychometric intelligence was positively associated with frontal-parietal theta coherence when measured during resting state (Anokhin et al., 1999; Granados-Ramos et al., 2019; Jaušovec & Jaušovec, 2000; Lee et al., 2012; Razoumnikova, 2003; Thatcher et al., 2005) as well as during task processing (Anokhin et al., 1999; Okuhata et al., 2009; Pahor & Jaušovec, 2016; Weiss et al., 2000). This indicates that individuals with higher psychometric intelligence exhibited a more synchronized network between frontal and parietal electrodes, which, in turn, reflects increased attention control and corroborates previous behavioral findings (Burgoyne et al., 2020; Heitz et al., 2005; Mashburn et al., 2020).

Also, in terms of temporal information processing, it was shown that performance differences could be explained by the involvement of attentional processes as described above in the extended pacemaker-accumulator models (Brown, 2008; Grondin, 2010; Matthews & Meck, 2016; Zakay & Block, 1996). However, no study to date investigated how these ongoing processes in the form of theta coherence can explain individual differences. There is only one study that investigated theta coherence during temporal information processing (Hoodgar et al., 2022). Moreover, they observed theta coherence during the encoding of a shorter (500 ms) and a longer interval (1 s) in a DD task. They could further show theta coherence between frontal and temporal electrodes during the encoding of a shorter interval (500 ms) and between frontal and temporal, central and temporal, central and occipital, and between temporal and occipital electrodes during the encoding of a longer duration (1000 ms). These connections were shown between the right and left hemispheres (e.g., Fp1-T8) and intrahemispheric (e.g., Fp1-T7), indicating possible hemispheric differences. However, as these results reflect a task approach and did not focus on performance-related differences in theta coherence, it remains to be seen how theta coherence can be linked to individual differences in temporal information processing.

3 Research Questions and Hypotheses

TRP has repeatedly been shown to be a significant predictor of psychometric intelligence (Haldemann et al., 2012; Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b). In this context, it was shown that TRP could explain differences in psychometric intelligence even beyond SIP (Helmbold et al., 2007; Pahud et al., 2018). This was interpreted in terms of the first part of the TRP hypothesis, namely, that individuals with higher TRP also process information faster. Furthermore, TRP was positively related to WMC (Troche & Rammsayer, 2009b) which was interpreted in terms of second aspect of the TRP hypothesis. It shows that individuals with a higher TRP, also coordinate their mental operations, which allows for a higher WMC, and, thus, a higher psychometric intelligence (Troche & Rammsayer, 2009b). Further studies investigating this relationship have not yet been published. Furthermore, apart from SIP and WMC, no other mechanism involved in information processing has been investigated yet in regard to the TRP hypothesis. Besides these behavioral aspects, it also still remains unknown to what extent individual differences could be reflected in an internal master clock. Its clock rate is supposed to be reflected in neural oscillations (Rammsayer & Brandler, 2002, 2007; Surwillo, 1968), however, no study to date has investigated a possible psychophysiological basis.

The overall aim of this dissertation was to strengthen and extend the TRP hypothesis on the behavioral and psychophysiological levels. To this end, four studies have been conducted, whose research questions and hypotheses are described in the following subsections. In Studies 1 and 3, the specific aspects of the TRP hypothesis were investigated in more detail by examining links to another information processing mechanism at the behavioral level with spatial suppression (Study 1) and the extent to which the coordination processes postulated by the TRP hypothesis are linked to the updating process in WM at the behavioral level (Study 3). Studies 2 and 4 investigated the possible psychophysiological basis of the internal master clock underlying TRP using EEG measurements during a resting state (Study 2) and a temporal information processing task (Study 4). Studies 1-3 were published in the following articles, and Study 4 reflects an additional analysis described in an unpublished manuscript. These three articles, as well as the unpublished manuscript, can be found in chapter 4.

Studies:

1. **Makowski, L. M.**, Rammsayer, T. H., Tadin, D., Thomas, P., & Troche, S. T. (2022). On the interplay of temporal resolution power and spatial suppression in their prediction of psychometric intelligence. *PLoS ONE, 17*(9), e0274809. https://doi.org/10.1371/journal.pone.0274809
2. **Makowski, L. M.**, & Troche, S. T. (2024). Can the resting state peak alpha frequency explain the relationship between temporal resolution power and psychometric intelligence? *Behavioral Neuroscience, 138*(1), 15–29. https://doi.org/10.1037/bne0000571
3. Troche, S. T., **Makowski, L. M.**, Pahud, O., & Rammsayer, T. H. (2024). Working memory updating as a mediator of the relation between temporal resolution power and psychometric intelligence. *Personality and Individual Differences, 220*, 112479. https://doi.org/10.1016/j.paid.2023.112479

4. **Makowski, L. M.** (2023). Examining the links between duration discrimination performance, gamma and theta coherence with regard to differences in psychometric intelligence. [Unpublished manuscript].

3.1 Study 1

Previous studies have repeatedly shown a positive association between TRP and psychometric intelligence (Haldemann et al., 2012; Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b). Besides TRP, another information processing mechanism, spatial suppression, has also been (positively) functionally linked to psychometric intelligence (Arranz-Paraíso & Serrano-Pedraza, 2018; Cook et al., 2016; Melnick et al., 2013). As TRP, spatial suppression also reflects a bottom-up mechanism that facilitates information processing and involves temporal information processing aspects (Melnick et al., 2013; Rammsayer & Brandler, 2007; Tadin, 2015). However, to the best of our knowledge, no study so far has examined to what extent these two mechanisms can contribute together to the understanding of individual differences in psychometric intelligence.

Based on this, Study 1 aimed to replicate the relationship between TRP and psychometric intelligence and to investigate how another information processing mechanism, spatial suppression, can contribute to the relationship between TRP and psychometric intelligence. As the spatial suppression index reflects a difference score, it might be attenuated by low reliability (Jensen, 1998) and influenced by task-independent processes (Schweizer, 2006b). To overcome this, the performance of the spatial suppression task was analyzed by fixed-links modeling, a particular form of confirmatory factor analysis (CFA; Schweizer, 2006b, 2006a). By this, a latent increasing and a latent constant variable were derived from the spatial suppression thresholds by fixating their factor loadings. This latent variable approach was also used by a previous study investigating the association between spatial suppression, SIP, and psychometric intelligence (Troche et al., 2018). Whereas the latent increasing variable was supposed to reflect spatial suppression, the latent constant variable was interpreted as reflecting motion processing speed. To this end, the following four hypotheses were examined:

- There is a positive relationship between TRP and psychometric intelligence.
- There is a positive relationship between spatial suppression and psychometric intelligence.
- There is a positive relationship between TRP and spatial suppression.
- TRP and spatial suppression contribute together to the explanation of

individual differences in psychometric intelligence.

3.2 Study 2

Based on Study 1, the aim of Study 2 was to replicate the association between TRP and psychometric intelligence and extend these findings to the psychophysiological level. Moreover, it was previously proposed that individual differences in TRP should be reflected by the rate of an internal master clock (Rammsayer & Brandler, 2002, 2007; Surwillo, 1968). The rate or ticking of this master clock, in turn, should be reflected by neural oscillations. Also, regarding individual differences in psychometric intelligence, it was proposed that neural oscillations are important for understanding why individuals with faster SIP also perform better in psychometric intelligence tasks (Jensen, 1982, 2006). Both theoretical frameworks emphasize the role of neural oscillations, particularly their speed. However, neither of them specifies how this could be measured at the psychophysiological level. Based on the speed aspect of the oscillation, the PAF could provide a possible candidate, as it shows individual differences in the Hz range (Angelakis, Lubar, Stathopoulou, et al., 2004; Drewes et al., 2022; Hilger et al., 2022), which in turn represents the speed of an oscillation (Cohen, 2014). In addition, previous studies have shown that the PAF is involved in information processing (Angelakis, Lubar, Stathopoulou, et al., 2004; Jann et al., 2010; Klimesch et al., 1996; Mierau et al., 2017; Samaha & Romei, 2023), and has been positively linked to psychometric intelligence (Angelakis et al., 2004; Anokhin & Vogel, 1996; Leno et al., 2021; Doppelmayr et al., 2002; Grandy et al., 2013) as well to the performance in an temporal information processing task (Samaha & Postle, 2015). However, there also other studies who could find no link between PAF and psychometric intelligence (Finnigan & Robertson, 2011; Ociepka et al., 2022; Pahor & Jaušovec, 2016; Posthuma et al., 2001; Trammell et al., 2017) as well as no link between PAF and temporal information processing performance (Glicksohn et al., 2009; Milton & Pleydell-Pearce, 2017; Venskus & Hughes, 2021). Methodological differences in previous studies might explain these inconsistencies. More specifically, previous studies differed in what resting state they measured PAF, how many resting states they used, and which electrode sites they focused on.

Based on the previous literature, Study 2 aimed to examine the association between PAF and TRP as well as between PAF and psychometric intelligence. Another objective was to investigate to what extent the PAF, as a reflection of the internal master clock, mediates the relationship between TRP and psychometric intelligence. For this purpose, the PAF was measured several times (eyes closed, eyes open before each of the three TRP tasks) at 64 electrodes. Then, for each measurement point (e.g., before the DD task), each resting state (eyes closed, eyes open) as well as for each electrode of the 64 electrodes, the variables were further reduced by exploratory factor analysis (EFA) as well as CFA into four latent PAF variables. Its association with TRP and psychometric intelligence was then examined by SEM. The analyses focused on examining the following four hypotheses:

- There is a positive relationship between TRP and psychometric intelligence.
- There is a positive relationship between TRP and PAF.
- There is a positive relationship between PAF and psychometric intelligence.
- PAF mediates the relationship between TRP and psychometric intelligence.

3.3 Study 3

As in Studies 1 and 2, also in Study 3, the aim was to provide evidence for a positive relationship between TRP and psychometric intelligence. As the second notion of the TRP hypothesis, which states that individuals with higher TRP also coordinate their mental operations more effectively and are thus better in psychometric intelligence tests (Rammsayer & Brandler, 2007), has only been investigated once before, a further aim was to extend this evidence. The previous study focused on the relationships of TRP and psychometric intelligence with WMC (Troche & Rammsayer, 2009b). They argued that the coordination of mental operations becomes more critical when the resources in the information processing system are limited, as is also the case with WMC. Based on this, the authors were able to demonstrate that a higher TRP facilitates the coordination of mental operations and thus also enables a higher WMC, which in turn could explain better performance in psychometric intelligence tests. However, as this study used a wide range of tasks to assess WMC, through which WMC was very closely linked to the implemented psychometric intelligence measures, further evidence on the second aspect of the TRP hypothesis is needed.

The main aim of the third study was to reexamine the second part of the TRP hypothesis. A WM updating task, the Stankov task, was used to measure coordination processes more precisely. Within such a task, information has to be maintained, retrieved, transformed, substituted, or removed from WM (Ecker et al., 2010). These processes need to be coordinated, which suggests that a WM updating might be more suitable to investigate the second part of the TRP hypothesis. Furthermore, WM updating has also been positively associated with psychometric intelligence (e.g., Oberauer et al., 2008; Wilhelm et al., 2013). To this end, the association between TRP, WM updating, and psychometric intelligence was examined using SEM. As in Study 1, we implemented a fixed-links modeling approach to derive two latent variables from the accuracy measures of the WM updating task: one with increasing factor loadings, reflecting WM updating, and one with constant factor loadings, reflecting individual differences unrelated to WM updating. The following four hypotheses were then examined by means of SEM:

- There is a positive relationship between TRP and psychometric intelligence.
- There is a positive relationship between WM updating and psychometric intelligence.
- There is a positive relationship between TRP and WM updating.
- WM updating (partially) mediates the relationship between TRP and psychometric intelligence.

3.4 Study 4

According to the TRP hypothesis, the relationship between TRP and psychometric intelligence should be based on differences in sensory acuity (Rammsayer & Brandler, 2002, 2007). In contrast to this notion, a previous study showed that attention control, a top-down process, could fully explain the relationship between general sensory discrimination ability and psychometric intelligence (Tsukahara et al., 2020). Based on this finding, it could be that the relationship between TRP and psychometric intelligence is not only due to the differences in a sensory process, such as the internal master clock but also due to differences in a top-down process, such as attention control. In line with this, previous studies could show that the extent of focused attention on task-relevant aspects in single temporal information processing was also crucial for task performance (Bausenhart et al., 2016; Ciria et al., 2019; Dyjas et al., 2012; Ogden, 2014; van Rijn, 2016). In this turn, it was even argued that the mechanism of the internal clock as a bottom-up mechanism interacts with attentional top-down processes during temporal information processing (van Rijn, 2016). Attention control has also been shown to play an important role regarding differences in psychometric intelligence. Moreover, it has been shown to have a positive influence on information processing, which in turn then led to better performances in psychometric intelligence tests (Burgoyne et al., 2020; Heitz et al., 2005; Kovacs & Conway, 2016; Mashburn et al., 2020).

To the best of our knowledge, no previous study has investigated to what extent attention control might be involved in the relationship between TRP and psychometric intelligence. Thus, Study 4 aimed to provide first evidence by investigating to what extent sensory processes and attention control are associated with task performance in a temporal information processing task and to what extent these associations are moderated by psychometric intelligence. To this end, a subsample of Study 2 with 50 individuals with higher and 50 with lower psychometric intelligence scores was chosen. Differences in ongoing sensory processes and attention control were examined by means of coherence analyses. In this context, previous could show that individual differences in sensory processing can be analyzed using coherence analyses within the gamma frequency band (Karakaş et al., 2001; Strüber & Herrmann, 2022; von Stein & Sarntheim, 2000). However, as none of these studies focused on individual differences in temporal information processing, it was not possible to deduce which electrode areas would be important to focus on. This information was taken from previous fMRI studies on temporal information processing, which were able to show that the temporal and parietal areas, in particular, should be important for differences in the sensory process during time processing (Matell & Meck, 2000; Meck, 2005; Nani et al., 2019). Regarding the differences in attention control, previous studies have shown that this can be studied with the theta coherence between the frontal and parietal electrodes (Basharpoor et al., 2021; Eschmann et al., 2020; Karakaş, 2020; Myers et al., 2021; Nurislamova et al., 2019; Sauseng et al., 2005, 2006, 2007; von Stein & Sarntheim, 2000). Based on these previous findings, differences in sensory processesing were analyzed using temporal-parietal gamma coherence (30-49 Hz), and differences in attention control were analyzed using frontal-parietal theta coherence (4-7 Hz) in Study 4. The following four hypotheses were expected and examined:

- Temporal accuracy, as measured with the DD task performance, was expected to be positively related to sensory processing, as measured with the temporal-parietal gamma coherence during the encoding phase of an auditory duration discrimination task.
- Temporal accuracy, as measured with the DD task performance, was expected to be positively related to attention control, as measured with the frontal-parietal theta coherence during the encoding phase of an auditory duration discrimination task.
- An interaction effect was expected for sensory processing (temporal-parietal gamma coherence) and psychometric intelligence on temporal accuracy, as measured with DD task performance. Moreover, a stronger relationship between temporal accuracy (DD task performance) and sensory processing (temporal-parietal gamma coherence) was expected for individuals with higher psychometric intelligence.
- An interaction effect was expected for attention control (frontal-parietal theta coherence) and psychometric intelligence on temporal accuracy, as measured with DD task performance. Moreover, a stronger relationship between temporal accuracy (DD task performance) and attention control (frontal-

parietal theta coherence) was expected for individuals with higher psychometric intelligence.

4 Articles

4.1 Article 1: On the interplay of temporal resolution power and spatial suppression in their prediction of psychometric intelligence

This article is published as:

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On the interplay of temporal resolution power and spatial suppression in their prediction of psychometric intelligence

Lisa M. Makowski[1], Thomas H. Rammsayer[1], Duje Tadin[2], Philipp Thomas[1], Stefan J. Troche[1*]

[1] Institute of Psychology, University of Bern, Bern, Switzerland
[2] Departments of Brain and Cognitive Sciences, Neuroscience, Ophthalmology and Center for Visual Science, University of Rochester, Rochester NY, USA

* Corresponding author
E-mail: stefan.troche@unibe.ch (S. J. Troche)

Abstract

As a measure of the brain's temporal fine-tuning capacity, temporal resolution power (TRP) explained repeatedly a substantial amount of variance in psychometric intelligence. Recently, *spatial suppression*, referred to as the increasing difficulty in quickly perceiving motion direction as the size of the moving stimulus increases, has attracted particular attention, when it was found to be positively related to psychometric intelligence. Due to the conceptual similarities of TRP and spatial suppression, the present study investigated their mutual interplay in the relation to psychometric intelligence in 273 young adults to better understand the reasons for these relationships. As in previous studies, psychometric intelligence was positively related to a latent variable representing TRP but, in contrast to previous reports, negatively to latent and manifest measures of spatial suppression. In a combined structural equation model, TRP still explained a substantial amount of variance in psychometric intelligence while the negative relation between spatial suppression and intelligence was completely explained by TRP. Thus, our findings confirmed TRP to be a robust predictor of psychometric intelligence but challenged the assumption of spatial suppression as a representation of general information processing efficiency as reflected in psychometric intelligence. Possible reasons for the contradictory findings on the relation between spatial suppression and psychometric intelligence are discussed.

Keywords: *psychometric intelligence, temporal resolution power, spatial suppression, speed of information processing*

Introduction

The *temporal resolution power (TRP) hypothesis* explains individual differences in psychometric intelligence by individual differences in the TRP of brain functioning [1]. Within this conceptual framework, TRP is assessed by the timing accuracy and temporal sensitivity in timing tasks such as temporal discrimination, temporal-order judgment, or temporal generalization [2]. Several studies demonstrated that a single latent variable accounted for a substantial portion of common variance in different measures of timing accuracy and temporal sensitivity [2–5]. This latent variable was interpreted as a measure of the brain's fine-tuning capacity purified from task-specific and error variance [2]. Furthermore, TRP was substantially related to psychometric intelligence, with common variance ranging from 22% [3] to 44% [4]. As an explanation for this relationship, the TRP hypothesis assumes that individuals with higher TRP process information faster and coordinate mental operations better than individuals with lower TRP. Both these factors should contribute to better performance on psychometric intelligence tests [5]. This idea was supported by previous studies. For example, Troche and Rammsayer [6] reported that higher TRP was associated with higher working memory capacity, which in turn led to higher psychometric intelligence. In two other studies, TRP effectively mediated the functional relationship between speed of information processing and intelligence [4,7]. Hence, higher TRP enables more accurate and, concurrently, faster information processing and, thus, more efficient information processing, which results in better performance on intelligence tests.

Over the last decade, another conceptual framework, referred to as *spatial suppression*, attracted attention due to its possible association with psychometric intelligence [8–10]. On the behavioral level, spatial suppression is evident as a progressively increasing difficulty in perceiving visual motion as stimulus size increases [11]. Spatial suppression is largely restricted to medium and high contrasts, and is particularly strong for briefly presented (e.g., 30 ms) moving grating stimuli [11–13]. This widely replicated result [14] is hypothesized to reflect visual suppression of background motion signals, which in turn promotes rapid segmentation of moving objects [15]. In a typical spatial suppression experiment, participants' task is to correctly identify the direction of the perceived stimulus motion. According to an adaptive algorithm, the presentation time increases after an incorrect response and decreases after a correct response. This results in a motion-direction discrimination threshold (MDD) defined as the shortest stimulus presentation time for which the motion direction could be correctly detected with a given probability [11,16,17]. Most interestingly, for high and medium contrast stimuli, the MDD thresholds dramatically increase with increasing stimulus size. In other words, a considerably longer presentation time is needed for larger than for smaller stimuli to correctly identify their motion direction [11]. This increase in MDD thresholds as a function of increasing stimulus size is referred to as spatial suppression. As a commonly used quantification, the spatial suppression index (SI) is computed by subtracting the MDD threshold value for the smallest from the duration threshold for the largest stimulus size used in a spatial suppression task [11,18–20].

On the neuronal level, spatial suppression has been linked to the function of antagonistic center-surround neurons located in the middle temporal visual area [12,13,15,20–23]. More specifically, the firing rate of these neurons decreases for large high-contrast motion stimuli that, in addition to stimulating the receptive field center, stimulate the antagonistic surrounding region. This results in a diminished neural response to large, high contrast moving stimuli and an overall poorer neural representation of such stimuli [11–13,20–23].

In a pioneering study, Melnick et al. [10] investigated the correlational relationship between spatial suppression and psychometric intelligence. In two experiments, they obtained substantial correlations of $r = .64$ ($N = 12$) and $r = .71$ ($N = 53$) between SI and psychometric intelligence. Thus, higher intelligence was associated with a more pronounced increase of the MDD threshold from small to large stimuli. Proceeding from these findings, Melnick et al. [10] put forward the idea that spatial suppression reflects the overall neural ability to suppress irrelevant information [14], which is crucial for efficient information processing and, consequently, may explain individual differences in psychometric intelligence [24–27]. More specifically, Melnick et al. [10] concluded that the link between stronger spatial suppression and better performance on intelligence tests indicates that spatial suppression is an index of more efficient information processing via suppression of irrelevant information, not just within visual processing per se but also more broadly.

Although this notion has been supported by two subsequent studies [8,9], it was at variance with two other ones. The study by Linares et al. [28] investigated the relationship between spatial suppression and intelligence using a between-group design that included a group of schizophrenia patients (N = 33) and a healthy control group (N = 31). The results revealed a link between spatial suppression and a measure of intelligence only in patients with schizophrenia, with no indication for such a relationship for the healthy control group. Furthermore, in a large-scale study with 177 young healthy adults, Troche et al. [29] also failed to confirm a direct functional relationship between spatial suppression and general mental ability.

As a possible explanation of individual differences in intelligence, there is a striking conceptual resemblance between the concepts of TRP and spatial suppression, at least at first glance. First, both are bottom-up approaches as they assume that basic functions of the brain lead to individual differences in higher-cognitive processing and, eventually, in psychometric intelligence. Second, TRP and spatial suppression, in a way, facilitate (or directly reflect) the efficiency of information processing which, in turn, is assumed to be an important aspect of mental ability. Third, both concepts comprise aspects of temporal information processing. While spatial suppression is derived from the time required to correctly identify the direction of perceived stimulus motion, the formation of TRP is based on temporal sensitivity and accuracy.

Despite these similarities, however, several important differences between both concepts become evident at second glance. First, the MDD thresholds heavily depend on (presentation) time required to correctly identify the motion direction of a stimulus, or in other words processing speed is the decisive component of this measure. Spatial suppression, however, is represented by the *difference* between the MDD thresholds for a large and a small stimulus. Therefore, processing speed, which might determine both thresholds, does not necessarily affect the difference between these thresholds. Given the above-outlined relationship between TRP and processing speed, TRP might be related to the thresholds but completely independent of spatial suppression. Second, although spatial suppression can also occur in different modalities, only spatial suppression as a visual phenomenon with its underlying neural mechanisms located in visual brain areas has so far been associated with psychometric intelligence [20,21]. The TRP-intelligence relationship, on the contrary, does not depend on the modality of a given timing task [3]. More specifically, Haldemann et al. [3] argued that temporal information is processed modality-specific at an initial stage but controlled by a superordinated amodal processing system at a second stage. Most importantly, it was this amodal temporal processing system that was responsible for the relationship between TRP and psychometric intelligence. Thus, while spatial suppression refers to a specific sensory process in the visual system, the scope of TRP is broader and not linked to modality-specific processes.

In view of the above-mentioned similarities and differences between both conceptual frameworks, the functional relationship between TRP and spatial suppression in predicting individual differences in psychometric intelligence remains completely undefined. Therefore, the main goals of the present study were (1) to provide additional evidence for an association between spatial suppression and mental ability and (2) to directly compare the functional relationships between TRP and intelligence as well as between spatial suppression and intelligence, respectively. Another aim of the present study was to systematically investigate the mutual interplay of TRP and spatial suppression in predicting individual differences in intelligence.

For these purposes, a latent variable approach was applied with both TRP and spatial suppression. TRP was represented as a latent variable derived from different timing tasks. For the representation of spatial suppression, we used a similar fixed-links modeling approach as Troche et al. [29]. With this approach, individual differences in the MDD thresholds can be divided into variance systematically increasing with increasing stimulus size and variance independent of stimulus size. Thus, the latent variable, describing the first kind of variance, can be interpreted as a reflection of genuine spatial suppression. The latent variable, representing the variance not varying with stimulus size, reflects individual differences in the time of stimulus presentation required to correctly detect the motion direction, irrespective of stimulus size [29]. Combining the measurement models of TRP and spatial suppression allowed for the investigation of their functional relationship. In a next step, using latent regression modeling, the relationships between TRP and the *g* factor of psychometric intelligence as well as between spatial suppression and the *g* factor were investigated separately to determine the amount of variance of intelligence shared with TRP and spatial suppression, respectively. Finally, both TRP and spatial suppression were concurrently submitted to the regression model to examine their unique and common variance shared with *g*.

Methods

Participants

From an original sample of 296 participants, 23 participants had to be removed due to incorrect test behavior or the results of an outlier analysis. The final sample consisted of 152 women and 121 men ranging in age from 18 to 30 years ($M_{age} = 21.6$; $SD = 2.7$ years). All had normal or corrected-to-normal vision and reported no current health issues. Regarding the educational background, 38% of the participants had finished vocational school, whereas 62% had higher educational training. At the time of the study, 47% of the participants were college students, 42% were working in a profession, 10% were still in high school, and 1% were unemployed. For their participation, they received 45 Swiss francs or course credit. All participants signed written informed consent prior to their participation. The study protocol was approved by the local ethics committee of the University of Bern (Faculty of Human Sciences; No. 2016-9-00005).

Measure of psychometric intelligence

To measure psychometric intelligence, we used a modified short version of the Berlin Intelligence Structure (BIS) test [30] (see also [7,29]). This version consisted of 18 subtests with six subtests assessing capacity-, six subtests assessing speed-, and six subtests assessing memory-aspects of psychometric intelligence. Each of these six-subtest bundles contained two figural, two numerical, and two verbal subtests. First, the raw scores of the subtests were z standardized before a mean score for capacity, speed, and memory was computed, respectively. Then, by means of a confirmatory factor analysis, the *g* factor was derived from the mean z scores of the three aspects of intelligence.

Spatial suppression task

The spatial suppression task was designed and used like the one in Melnick et al. [10]. Our goal was to closely match our task to Melnick et al. [10], both in task design and in the experimental equipment. The highest contrast was set to 42%, and the task was presented using a 360 Hz DLP projector (1280 x 720 resolution, 113.7 cd/m^2 background) as in the study by Melnick et al. [10]. The task was programmed with Matlab [31] to present brief visual grating-like stimuli with a spatial frequency of 1 cycle/°. These stimuli either moved leftward or rightward on a natively linearized display (178 cd/m^2 background, 2 cd/m^2 ambient illumination) with a constant moving speed of 4.8°/s. Four stimulus sizes were used, subtending a visual angle of 1.8°, 3.6°, 5.4°, and 7.2°, respectively. The stimulus size was specified by stationary raised cosine spatial envelopes through which moving gratings were shown and, thus, defined as the visible stimulus diameter (visibility defined as local contrast higher than 1%). The stimulus duration was determined as the full width at half-height of the trapezoidal temporal envelope [20]. To keep the viewing distance constant at 146 cm for each subject, a chin rest was used. Participants gave their responses by using the left and the right arrow keys on a computer keyboard.

At the beginning of the task, participants performed 180 practice trials. Then they completed three blocks with 44 trials per stimulus size, leading to a total of 528 trials and a test duration of about 26 minutes. Within each block, stimulus size varied randomly. Each trial started with a fixation circle, followed by a moving stimulus that was presented in the center of the monitor. Participants then indicated the perceived direction of the drifting grating by pressing the left arrow key when they had perceived a leftward movement and the right arrow key for a perceived rightward movement. They were asked to answer as accurately as possible, with no emphasis on response speed. After their answer, participants received auditory feedback (a 50-ms sine wave tone of 2900 Hz) for a correct answer and no feedback for an incorrect answer. The initial presentation time for each stimulus condition was 80 ms. The presentation time of the next stimulus with the same size was adapted depending on the previous response. In the case of a correct response, presentation time decreased, and after an incorrect response, it increased according to the adaptive Bayesian QUEST-procedure proposed by Watson and Pelli [32]. Based on this procedure, in each block, two estimates of the 82% motion-direction detection threshold were gathered per stimulus size for each participant resulting in six estimates of the threshold for each stimulus size. Because the QUEST procedure requires logarithmic values, the estimated thresholds for motion perception represented the $\log_{10}$ value for presentation time required to produce 82% correct responses, with smaller thresholds indicating better performance. Of the six estimates, the highest and lowest estimates for each stimulus size per individual were discarded, resulting in four remaining thresholds per stimulus size for each individual (see [10]). These four remaining thresholds were then averaged separately for each stimulus size, resulting in one threshold value per stimulus size.

The spatial suppression index (SI) was calculated for each participant by subtracting the $\log_{10}$ of the mean MDD threshold of the smallest stimulus size from the $\log_{10}$ of the mean threshold of the largest stimulus size [19].

Assessment of temporal resolution power

Temporal resolution power was assessed with the following four timing tasks, which were programmed and presented with E-Prime 2.0 [33].

Duration discrimination tasks

In the duration discrimination task with empty auditory intervals (DDE), the intervals were marked by a 3-ms onset and 3-ms offset white noise burst (DDE). These auditory intervals were presented via headphones at an intensity of 70 dB.

The task consisted of 64 trials. Each trial contained a standard interval with a duration of 50 ms and a comparison interval of varying duration. The two intervals were separated by a 900-ms interstimulus interval. In one series of 32 trials, the comparison interval was shorter than the standard interval. In another series of 32 trials, the comparison interval was longer. The two series were interleaved, and the order of standard and comparison interval was randomized and balanced. For each trial, participants' task was to indicate whether the first or the second interval was longer by pressing a designated key on the keyboard. They received visual feedback for 1500 ms on the center of the monitor screen. After an intertrial interval of 600 ms, the next trial started. Following the adaptive weighted-up-down procedure [34], for the first until the sixth trial, the difference between standard and comparison interval of the next trial was increased by 9 ms when the response had been incorrect and decreased by 3 ms when the previous response had been correct. For the seventh until 32nd trial, the respective steps were 6 ms and 2 ms. With this procedure, the series of 32 trials with the comparison interval being shorter than the standard interval resulted in the 25%-difference threshold (x.25), while the other series resulted in the 75%-difference threshold (x.75). Both thresholds were computed across the last twenty trials of the respective series. As a measure of performance, the difference limen (DL) was calculated by half of the interquartile range [(x.75-x.25)/2], with better performance indicated by smaller values [35].

An additional duration discrimination task (DDF) was used, which had the same procedure as described above for the DDE. However, the stimuli were filled auditory intervals (DDF) of white-noise bursts presented at an intensity of 70 dB. Written instructions and training trials preceded both tasks, which lasted about 7 minutes each.

Temporal generalization task

The temporal generalization task (TG) consisted of 64 trials with a total duration of 5 minutes. The task began with a learning phase in which participants were presented with a standard duration, which was a 75-ms white-noise burst at an intensity of 70 dB presented via headphones. The standard duration was presented five times, and participants were instructed to memorize the duration. Afterward, the experimental phase began, and participants were randomly presented either with the standard duration (75 ms) or with an alternative duration (42 ms, 53 ms, 64 ms, 86 ms, 97 ms, or 108 ms). After each stimulus presentation, they had to decide whether it was the standard stimulus or not by pressing designated keys with “Yes” or “No” on a keyboard. After their response, they received visual feedback in the monitor center for 1500 ms, followed by an intertrial interval of 700 ms. The experimental phase consisted of eight blocks. Within each block, the standard duration (75 ms) was presented twice and each of the six non-standard durations once. The order of the durations was randomized in each block.

As a performance measure, the index of response dispersion was computed by dividing the relative frequency of “Yes” responses to the standard duration by the total of the relative frequencies of “Yes” responses to all seven stimulus durations [36]. A value close to 1 indicates that all the “Yes” answers are closely gathered around the standard duration. For the further analyses, the values of the index of response dispersion were inverted.

Rhythm perception task

The rhythm perception task (RP) consisted of 64 trials. In each trial, a rhythmic pattern of six 3-ms white-noise bursts was presented via headphones at an intensity of 70 dB, leading to five beat-to-beat intervals. Four of these five auditory intervals were held constant with 150 ms, whereas one interval had a variable duration (150 + x) with an initial duration of x = 20 ms. In one series of 32 trials, the third beat-to-beat interval was variable, while in the other series of 32 trials, it was the fourth interval. The two series were presented in interleaved order. For each series, the value of x was adapted according to the weighted-up-down procedure [34]. Thus, depending on the correctness of the previous response, the interval was increased by 4 ms after a correct response and decreased by 12 ms after an incorrect response. After the presentation of the rhythmic pattern, participants had to decide if they had perceived the pattern as regular or irregular by pressing one of two designated keys. Since all patterns had been irregular, participants received no feedback after their response. Instead, the next trial started 700 ms after the response to the preceding trial.

The 75% threshold for the detection of irregularity was calculated for each series and, afterwards, the two thresholds were averaged as a measure of performance. The task lasted about 5 minutes, and written instructions as well as training trials were presented prior to the actual task.

Time course of the study

The study consisted of two sessions. In the first session, participants completed the psychometric intelligence test (BIS) with a duration of about 90 minutes. In the second session, the experimental tasks were administered. The second session always started with the spatial suppression task. Afterwards, the timing tasks were administered in a balanced order. Finally, two further experimental tasks were conducted, which are irrelevant for the present purpose. The second session lasted about 120 minutes. Both sessions were separated by about one week.

Data Analysis

The following analyses were conducted with R [37], Version 4.1.0 and R-Studio [38], Version 1.4.1106 using the Hmisc package [39], the rstatix package [40], the ez package [41], the GPArotation package [42] and the lavaan package [43]. Before analyzing the data set, an interindividual outlier detection was computed. For the TRP tasks and for the first threshold of the spatial suppression task (1.8°), participants were considered outliers and removed from the dataset when they exceeded the mean by three standard deviations. This resulted in a final sample of 273 participants. Then, descriptive statistics were analyzed, followed by correlation analyses and a one-way ANOVA by including the logarithmic thresholds of the spatial suppression task as four levels of a repeated-measures factor. Then, the measurement models for *g*, TRP, and spatial suppression were fit separately, and afterwards, the structural equation models were computed. All models were estimated with robust maximum likelihood estimation. As for fit indices, χ^2 values, comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root mean squared residual (SRMR) were determined. If a model fits the data well, then the χ^2 value should be small and not statistically significant [44]. However, the χ^2 statistic is sensitive to sample size, and its *p* value might be significant, although the predicted model represents the data well [44,45]. Therefore, we report χ^2(df) but do not consider it in the model evaluation. The other indices were interpreted as good (or acceptable) with the following values [46]: a CFI $\geq .95$ ($\geq .90$), RMSEA $\leq .05$ ($\leq .08$) and SRMR value $\leq .08$ ($\leq .10$).

Results

Descriptive statistics

Table 1 shows the descriptive statistics for the four thresholds of the spatial suppression task and for the four timing tasks. In the spatial suppression task, the MDD thresholds increased with increasing stimulus size (also see Fig 1). To investigate if this increase in presentation time with increasing stimulus size was significant, a one-way ANOVA was conducted by including the thresholds of the spatial suppression task as four levels of a repeated-measures factor. Because the Mauchly’s test showed a violation of sphericity, the Greenhouse-Geisser correction with $\varepsilon = 0.722$ was applied. ANOVA revealed a significant main effect, $F(2.16, 588.87) = 580.137$, $p < .001$, $\eta^2 = .273$. Bonferroni-corrected pairwise *t* tests further revealed significant differences between all four thresholds (all *p*s < .001). Thus, participants needed a longer presentation time to correctly identify the motion direction when the stimulus became larger. Overall, both the pattern of results and actual thresholds were highly consistent with the results reported in Melnick et al. [10].

Table 1. Descriptive statistics for the motion-direction detection thresholds in the four conditions of the spatial suppression task, for the difference limina in the duration discrimination tasks (DDE, DDF), for the dispersion index in the temporal generalization task (TG), and the mean 75% difference threshold in the rhythm perception (RP) task in the sample of 273 participants.

	M	*SD*	*Min*	*Max*	*Skewness*	*Kurtosis*
Spatial suppression task						
1.8° condition [ms]	44.69	14.22	15.71	83.63	0.25	-0.48
3.6° condition [ms]	53.86	21.43	16.76	133.64	0.68	0.57
5.4° condition [ms]	72.86	34.02	13.38	277.78	1.75	6.25
7.2° condition [ms]	91.45	47.32	20.90	459.23	2.75	14.39
TRP tasks						
DDE [ms]	18.33	8.22	4.95	51	1.22	1.80
DDF [ms]	8.81	3.26	3.60	23	1.67	3.82
TG [dispersion index]	0.66	0.12	0	0.97	-1.17	4.59
RP [ms]	55.90	22.43	7.18	128	1.04	0.63

TRP tasks = Temporal Resolution Power tasks, DDE= Duration Discrimination with empty intervals, DDF = Duration Discrimination with filled intervals, TG = Temporal Generalization Task, RP = Rhythm Perception Task. The presented raw values of the spatial suppression task were each multiplied by 2.5 [10].

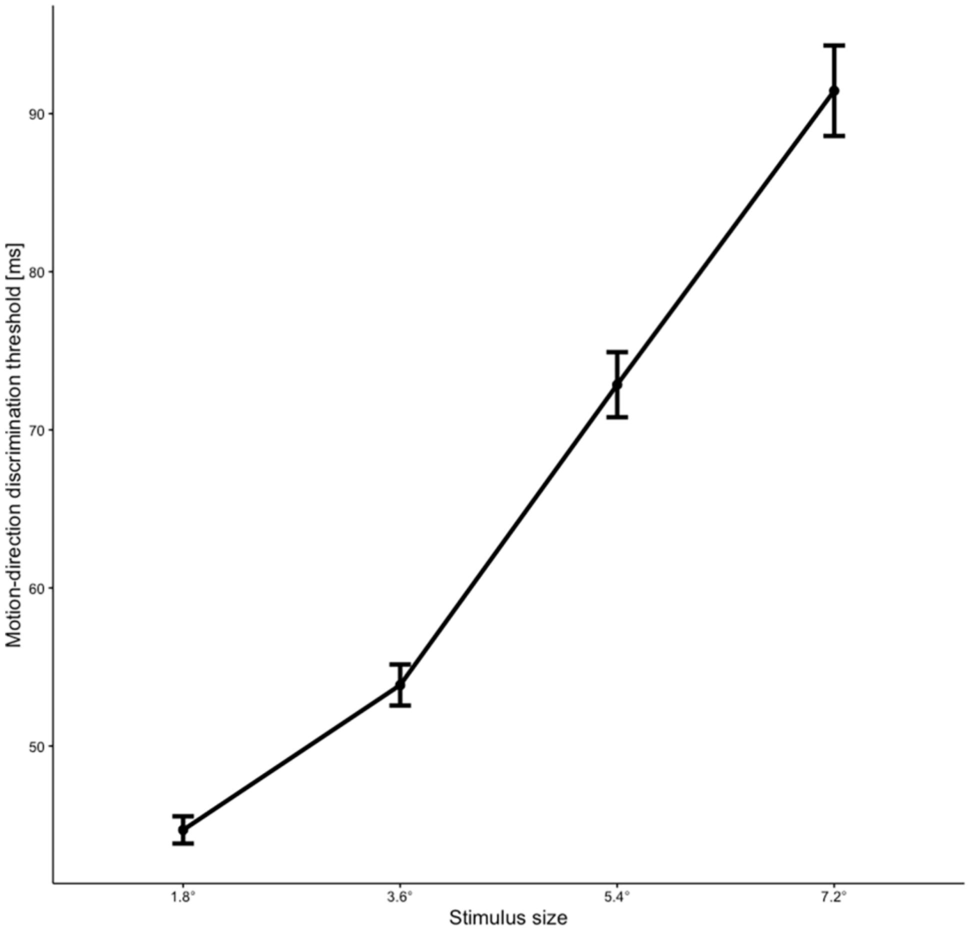

Fig 1. Line plot of the mean thresholds (ms) concerning the four conditions (stimulus sizes) in the spatial suppression task, showing the mean per stimulus size and its standard errors of mean in 273 participants. For better illustration, the raw values of the presented mean thresholds were each multiplied by 2.5 [10].

The spatial suppression index as the difference between the MDD threshold in the 7.2° and the 1.8° condition of the spatial suppression task ranged from -.036 to 1.000 (M = .29; SD = .15). Although the spatial suppression effect showed large interindividual differences, it was positive in 99% of the participants.

Correlational analyses

BIS-Capacity, BIS-Speed, and BIS-Memory correlated positively and significantly with each other ($r_{\text{BIS-Capacity – BIS-Speed}} = .51$, $r_{\text{BIS-Capacity – BIS-Memory}} = .46$, $r_{\text{BIS-Memory – BIS-Speed}} = .39$, all *p*s < .001), suggesting a common source of variance. Therefore, a one-factor model was computed by means of a confirmatory factor analysis (CFA). Due to only three manifest variables, the model was exactly identified, resulting in a perfect model fit [44]. McDonald's omega coefficient was $\omega = 0.72$ for the *g* factor extracted from BIS-Capacity, BIS-Speed, and BIS-Memory. The factor scores on this common factor were extracted and interpreted as individual differences in the *g* factor of psychometric intelligence, which were submitted to the following correlational analyses.

As can be taken from Table 2, the MDD thresholds in the four conditions of the spatial suppression task correlated positively with each other. Similarly, positive correlations were also obtained among performance measures in the four timing tasks. Furthermore, performance measures of the four timing tasks correlated significantly with all MDD thresholds of the spatial suppression task.

Table 2. Pearson correlations between psychometric intelligence (g factor), spatial suppression task, spatial suppression index, and temporal resolution power tasks.

	g factor	Spatial suppression task					TRP tasks			
Task		1.	2.	3.	4.	5.	6.	7.	8.	9.
Spatial suppression task										
1. 1.8°	-.17**									
2. 3.6°	-.24***	.83***								
3. 5.4°	-.23***	.69***	.84***							
4. 7.2°	-.26***	.63***	.76***	.88***						
5. SI	-.17**	-.16**	.16**	.45***	.67***					
TRP tasks										
6. DDE	-.24***	.15*	18**	.13*	.14*	.04				
7. DDF	-.20***	.18**	.18**	.18**	.20***	.09	.36***			
8. TG	-.34***	.20***	.20***	.19**	.19**	.05	.25***	.34***		
9. RP	-.24***	.14*	.21***	.22***	.20***	.12	.26***	.17**	.16**	

N = 273. TRP tasks = Temporal Resolution Power tasks, DDE = Duration Discrimination with empty intervals, DDF = Duration Discrimination with filled intervals, TG = Temporal Generalization Task, RP = Rhythm Perception Task. * $p < .05$, ** $p < .01$, *** $p < .001$.

The *g* factor scores correlated negatively with the four MDD thresholds and the performance measures from the four timing tasks (see Table 2). Since lower thresholds in the timing tasks and the spatial suppression task were indicative of better performance, the negative correlations pointed to positive relationships between psychometric intelligence and performance on the timing tasks as well as the spatial suppression task. Surprisingly, SI was negatively correlated with psychometric intelligence, indicating that higher psychometric intelligence was associated with a smaller SI. This correlational relationship is illustrated as scatterplot in Fig 2. Eventually, in contrast to the MDD thresholds, the SI was not significantly correlated with performance measures from the four timing tasks.

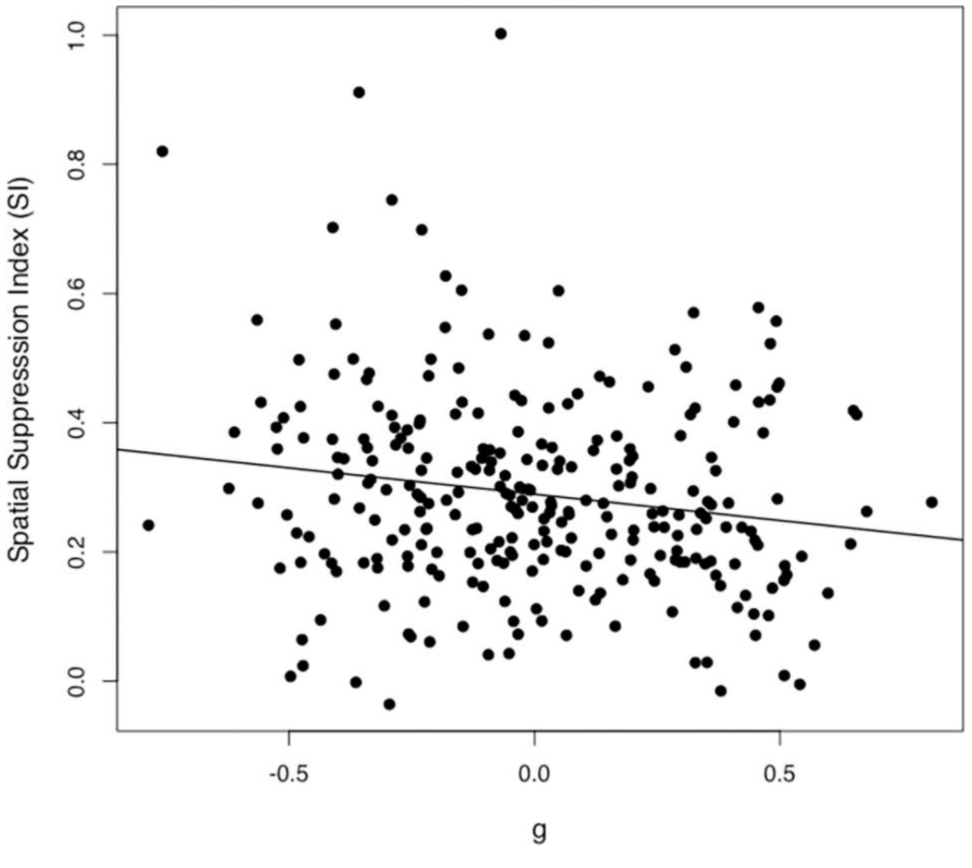

Fig 2. Scatterplot of the relationship between spatial suppression (spatial suppression index) and *g* in the sample of 273 participants.

Measurement models

The TRP factor was derived as a latent variable from the four timing tasks. A one-factor confirmatory factor analysis resulted in a good fit, $\chi^2(2) = 2.770$, $p = .250$, CFI = .990, RMSEA = .038, SRMR = .024. The factor loadings of all four tasks were significant (all *p*s <

.001) ranging from .338 for the rhythm perception task to .632 for the duration discrimination task with filled intervals. McDonald's omega coefficient was $\omega = 0.59$ for the TRP factor.

A congeneric model of spatial suppression was first constructed to represent spatial suppression at the latent level with one factor. Confirmatory factor analysis showed a bad model/data fit, $\chi^2(2) = 79.777$, $p < .001$, CFI = .892, RMSEA = .377, except for SRMR = .047. Therefore, a fixed-links modeling approach was used to derive two latent variables from the spatial suppression task (see [29]). The factor loadings of the first latent variable were fixed to the constant value of one for all four thresholds. Therefore, this latent variable is also referred to as "constant latent variable" (SSC in Fig 3). For the second variable, referred to as the "increasing latent variable" (SSI in Fig 3), the factor loadings were set to increase linearly with 0, 1, 2, and 3, respectively, as in the study by Troche et al. [29]. The correlation between SSI and SSC was set to zero. The resulting model was better than the congeneric model but still failed to provide a good description of the data, $SB\chi^2(4) = 41.287$, $p < .001$, CFI = .948, RMSEA = .185, SRMR = .074. According to the modification indices (M.I.) provided by the lavaan package, a residual correlation between the second threshold condition (3.6°) and the third threshold condition (5.4°) could improve the fit of the model (M.I. = 51.167), suggesting that these two stimulus sizes might have something in common that the latent variables could not explain. When the residual correlation between the second and third threshold condition was allowed, the variances of the first and fourth thresholds showed negative values. Therefore, in the next step, the variances of the first and fourth threshold condition were restricted to values greater than zero. This final model then revealed an acceptable fit according to CFI (= .991) and SRMR (= .066), while the RMSEA with .087 was slightly larger than .080, $SB\chi^2(3) = 9.162$, $p = .027$. The latent variances of both SSC ($\varphi = .022$, $z = 10.345$, $p < .001$) and SSI ($\varphi = .003$, $z = 7.771$, $p < .001$) were statistically significant. This indicated that both latent variables described a substantial portion of systematic individual differences in the thresholds of the spatial suppression task. When comparing the final model to the congeneric one-factor model, the final model showed a lower AIC ($AIC_{final} = -1672.068$ compared to $AIC_{congeneric} = -1571.579$), suggesting that the two-factor solution with the added residual correlation between the second and third threshold condition represented the data better than the one-factor solution. McDonald's omega coefficients were $\omega = 0.94$ for SSC and $\omega = 0.81$ for SSI. To note, SSI represents individual differences in the increase of the MDD thresholds with increasing stimulus size (and, thus, the spatial suppression effect). SSC, on the contrary, reflects general differences in the time required to correctly identify the direction of stimulus movement irrespective of stimulus size.

Structural equation models

To examine and replicate the relationship between the TRP factor and psychometric intelligence, the measurement models of TRP and *g* were combined, and the *g* factor of psychometric intelligence was regressed on the TRP factor. The model showed an acceptable to good model fit, $SB\chi^2(13) = 23.904$, $p = .032$, CFI = .960, RMSEA = .055, SRMR = .040, and TRP predicted the *g* factor of psychometric intelligence with $\beta = -.572$, $p < .001$, thus, explaining 33% of its variance.

The combination of the fixed-links measurement model of spatial suppression and the *g* factor measurement model led to an acceptable to well-fitting model, $SB\chi^2(13) = 27.146$, $p = .012$, CFI = 0.987, RMSEA = 0.063, SRMR = 0.058. Both SSI, $\beta = -.244$, $p < .001$, and SSC, $\beta = -.236$, $p = .001$, were negatively associated with psychometric intelligence. Thus, participants with higher values in *g* had a less pronounced spatial suppression effect as indicated by the SSI and, concurrently, generally lower MDD thresholds as indicated by the SSC. Together the two latent variables explained 11% of the variance in *g*.

To investigate the interplay between psychometric intelligence, TRP, and spatial suppression, the relationship between TRP and spatial suppression was examined by combining the above-described measurement models for TRP and spatial suppression and allowing for correlations between TRP and both latent variables extracted from the spatial suppression conditions. The resulting model revealed a good fit, $SB\chi^2(19) = 27.249$, $p = .099$, CFI = .992, RMSEA = .040, SRMR = .050. TRP was significantly and positively correlated with both SSC, $r = .342$, $p < .001$, and SSI from the spatial suppression task, $r = .177$, $p = .022$. Thus, higher TRP was related to faster motion-direction detection (irrespective of stimulus size) and less spatial suppression.

Finally, the prediction of psychometric intelligence by concurrently considering TRP and spatial suppression was examined. The model (Fig 3) showed a good fit, $SB\chi^2(40) = 58.187$, $p = .031$, CFI = .985, RMSEA = .041, SRMR = .050. The TRP factor was still significantly associated with psychometric intelligence, $\beta = -.535$, $p < .001$. However, SSC, $\beta = -.058$, $p = .432$, and SSI from the spatial suppression task, $\beta = -.140$ $p = .057$, did no longer significantly predict psychometric intelligence when TRP was included in the model. Moreover, TRP correlated significantly with SSC, $r = .353$, $p < .001$, and SSI, $r = .180$, $p = .022$. The standardized factor loadings and regression parameters are presented in Fig 3.

Thus, the variance SSI and SSC shared with psychometric intelligence could be fully explained by TRP.

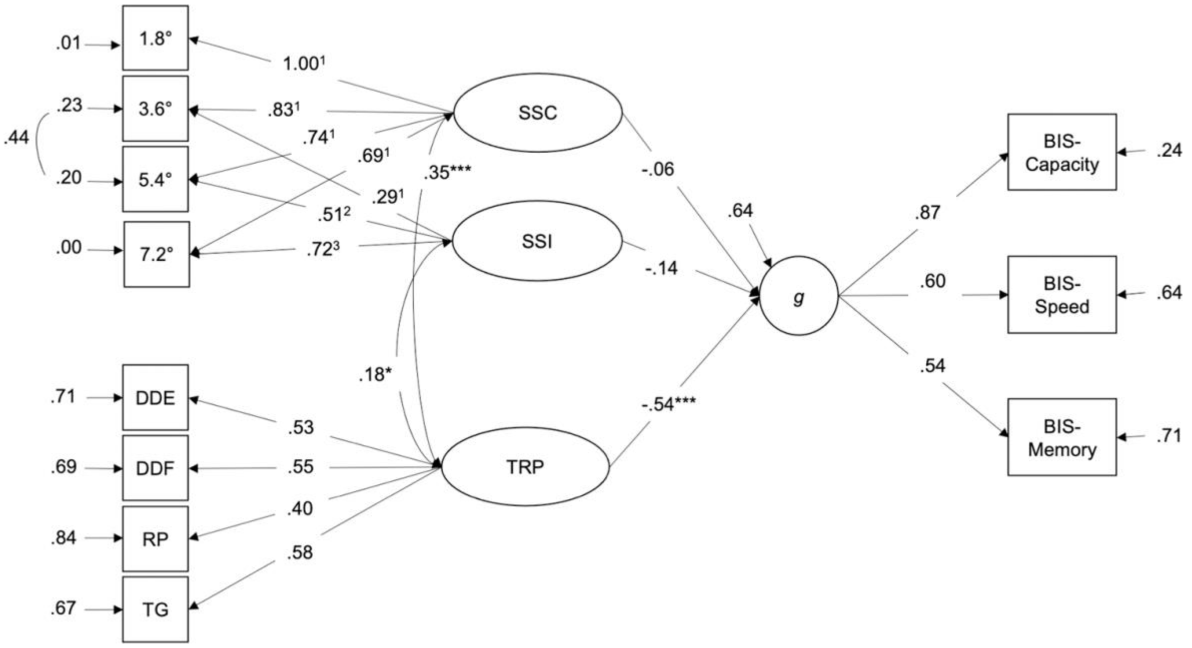

Fig 3. Final model illustrating the interplay between spatial suppression, TRP, and the *g* factor of psychometric intelligence in $N = 273$ participants. Two latent variables were derived from the spatial suppression task, one representing individual differences in spatial suppression (SSI) and the other representing individual differences in motion-direction discrimination thresholds independent of stimulus size (SSC). Standardized factor loadings and regression coefficients are presented and unstandardized factor loadings for the spatial suppression measurement model are given in superscript. * $p < .05$, *** $p < .001$.

Discussion

The major aim of the present study was to provide further evidence for the functional relationship between psychometric intelligence, on the one hand, and spatial suppression as well as TRP, on the other one. Furthermore, we focused on the mutual interplay of TRP and spatial suppression in explaining variance in psychometric intelligence. The results showed that spatial suppression was negatively related to psychometric intelligence, which contrasts with previous findings of a positive relationship (e.g., [10]). The negative correlational relationship between TRP and psychometric intelligence indicated that higher TRP, and thus higher timing accuracy and temporal sensitivity, was associated with higher psychometric intelligence confirming previous studies (e.g., [7]). Moreover, TRP and spatial suppression were not related at the manifest level but weakly at the latent level, suggesting that they represent widely but not completely independent processes. Higher TRP, however, was moderately related to a shorter time required to correctly identify motion direction irrespective of stimulus size. When psychometric intelligence was regressed on TRP and spatial suppression concurrently, only TRP still explained a significant amount of variance in psychometric intelligence.

Some previous studies reported a positive association between spatial suppression and psychometric intelligence, so that individuals with higher intelligence had a larger spatial suppression effect than individuals with lower intelligence [8–10]. These results suggested that more time was required to identify the correct direction of movement as stimulus size increased and that this was particularly true for individuals with higher (compared to lower) intelligence. In the present study, however, we found a negative relationship between psychometric intelligence and the four MDD thresholds in the spatial suppression task as well as the spatial suppression effect. This result held for the SI as a manifest variable as well as for the SSI latent variable in the measurement model of spatial suppression, which considered the increase of the MDD thresholds with increasing stimulus size across all four conditions of the spatial suppression task.

Procedural reasons for the contradictory findings of a negative relationship between spatial suppression and intelligence in the present study and the positive relationship in previous studies can be largely ruled out. We used the same software and hardware as in the second study by Melnick et al. [10]. The only difference was that our spatial suppression task consisted of four (instead of three) stimulus-size conditions with an additional stimulus size of 5.4°. The 1.8°, 3.6°, and 7.2° conditions were also used in the second study by Melnick et al. [10] so that the smallest and the largest stimulus size were identical in the two studies. However, Melnick et al. [10] included a practice session on a separate day, while our participants had a practice session on the day of experimental testing. In unpublished results, Tadin found that practice on a separate day led to less noisy data but had no effect on average thresholds and associated SIs. The fact that both the MDD thresholds as well as their increase with stimulus size were very similar in Melnick et al.’s [10] and the present study corroborated the reliability and replicability of the spatial suppression effect. Its correlation with intelligence, however, seems to be less replicable.

Arranz-Paraiso and Serrano-Pedraza [8] put forward the idea that the lower intelligence level in their sample compared to Melnick et al.’s [10] sample might have led to the weaker (but still positive) relationship between intelligence and spatial suppression in their study. Proceeding from this idea, we reanalyzed our data and submitted only half of the sample with higher psychometric intelligence to the analyses. Even in this subsample with higher intelligence, the spatial suppression index (as well as the four thresholds) still correlated negatively with intelligence, but no longer significantly (r = -.08, p = .382). Thus, the level of intelligence could not explain the difference between our results and Melnick et al.'s [10] results. Furthermore, when we correlated spatial suppression separately with figural and verbal intelligence subtests, both aspects of intelligence were negatively related to spatial suppression. Thus, the content-related aspects of the intelligence tests in the present and the previous studies were also unlikely to account for the different results.

As reviewed in Tadin [14], psychiatric conditions might influence the effect of spatial suppression. A history of major depression, a current schizophrenia diagnosis, or an autism diagnosis have been linked to variations in the strength of spatial suppression. In the present study and the study by Troche et al. [29], however, participants self-reported not to suffer from these psychiatric conditions so that a potential influence of these conditions on the correlation between spatial suppression and psychometric intelligence is unlikely.

A key difference between our study and the two experiments in Melnick et al. [10] was participants' age distribution. This might be important given that several studies showed a negative relationship between age and the spatial-suppression effect [15,47–49]. While the sample in Melnick et al.'s [10] first experiment had a mean age of 36.0 (± 7.2) years and in the second experiment of 33.1 (± 13.4) years, participants' mean age in the present study was 21.6 (± 2.7) years. When we investigated the influence of age on spatial suppression in the present sample, there was no evidence of any influence of age on spatial suppression, probably because the age range was quite limited with all participants younger than 30 years and 80% of the sample aged between 18 and 24 years. A similarly young sample was investigated by Troche et al. [29], who also did not observe a positive correlation between spatial suppression and psychometric intelligence. Thus, age-related changes in spatial suppression for participants older than 30 years could not be examined in the present study and the study by Troche et al. [29] so that age might still account for the differences between our results and the results by Melnick et al. [10]. However, Arranz-Paraiso and Serrano-Pedraza [8] as well as Cook et al. [9] also examined participants younger than 30 years and, similar to Melnick et al. [10], observed a positive correlation between psychometric intelligence and spatial suppression. The 31 healthy controls in the study by Linares et al. [28], on the other hand, had a mean age of 38.6 (± 13.8) years and the spatial suppression was unrelated to psychometric intelligence in this sample. Thus, age might be a possible explanation for the inconsistent findings among the relevant studies, but a clear pattern is difficult to discern. It can be stated, however, that the large sample sizes in the present study and the study by Troche et al. [29] strongly argue against a positive link between spatial-suppression strength and psychometric intelligence in adults younger than 30 years.

Another difference between our study and other studies on the relation between intelligence and spatial suppression is the measure of intelligence. Here, we used an adapted form of the BIS test as intelligence measure. In contrast, Melnick et al. [10] used the Wechsler Adult Intelligence Scale (WAIS; short form of WAIS-III [50] in Study 1, full version of WAIS-IV [51] in Study 2) and Arranz-Paraiso and Serrano-Pedraza [8] the Reynolds Intellectual Assessment Scales and Screening (RIAS [52,53]). Thus, at first glance, differences in the way of measuring intelligence cannot be ruled out to account for the divergent relations to spatial suppression. However, as shown by Johnson et al. [54], general intelligence in the sense of the *g* factor as a latent variable shows a high stability across different intelligence tests. From this perspective, it seems unlikely that the way of measuring intelligence is a significant reason for the divergent results.

From a statistical point of view, there are further reasons that could account for the inconsistent results on the relationship between spatial suppression and psychometric intelligence. Regarding the sample size, two studies used small sample sizes (N = 9 in Cook et al. [9]; N = 12 in Melnick et al. [10], Study 1) and two studies medium sample sizes (N = 50 in Arranz-Paraiso and Serrano-Pedraza [8]; N = 53 in Melnick et al. [10], Study 2). All these studies reported a positive correlation between spatial suppression and psychometric intelligence. Linares et al. [28] observed no significant correlation between spatial suppression and intelligence in 31 healthy adults. This latter result was in line with Troche et al. [29], who could not confirm a functional relationship in a sample of 177 participants. The present study with its 273 participants is the only one that even observed a negative (albeit weak) correlational relationship. Thus, the studies, which reported a positive correlation between spatial suppression and psychometric intelligence used rather small samples. This is highly critical given that small sample sizes lead to large confidence intervals around correlations [55]. This problem may be illustrated with Arranz-Paraiso and Serrano-Pedraza's [8] data. In this study, general intelligence correlated significantly neither with the MDD threshold for a small stimulus of 0.7°, $r = -.213$, $p = .150$, nor with the MDD threshold for a large stimulus of 6°, $r = .255$, $p = .083$. Given the sample size of N = 47, the 95% confidence intervals ranged from -.47 to +.08 and from -.03 to .51, respectively. Thus, the two correlations did not significantly differ from zero but reached by chance a negative and a positive value, respectively. At this point it is important to note that SI was calculated as the difference between the MDD thresholds for the large stimulus (minuend) and the small stimulus (subtrahend). With this operationalization, the weak (and by chance) positive correlation between the minuend and intelligence was enhanced by the weak (and by chance) negative correlation between the subtrahend and general intelligence. As a consequence, the positive correlation between SI and intelligence reached now statistical significance. This significant correlation, however, seems to be spurious when it is caused by random variation of the correlations between MDD thresholds and general intelligence.

In both the present study and the study by Troche et al. [29] the large sample sizes might have avoided such random variation in the correlation coefficients. Instead, relatively small but significant negative correlations between all four MDD thresholds and intelligence were obtained ranging from r = -.17 to -.26 in the present study and from r = -.16 to -.19 in the study by Troche et al. [29]. If we assume that due to the large samples in the latter two studies, the observed correlations between MDD thresholds and intelligence came close to their true values, which did not differ actually, the SI-intelligence correlation was probably less inflated by random variation than in studies with smaller samples. In the present study, the correlations between intelligence and the MDD thresholds for the smallest and for the largest stimulus did not differ significantly but the latter was more negative than the former one. This small difference was apparently large enough to cause a negative correlation between intelligence and spatial suppression – regardless of whether spatial suppression was measured as SI difference score or as SSI latent variable. Thus, the negative correlation between intelligence and spatial suppression in the present study might be as spurious as the positive correlations reported in other studies and just the result of small and unsubstantial differences between the correlations of intelligence and MDD thresholds for large and for small stimuli. In any case, against the background of the present pattern of results a general *positive* association between spatial suppression and psychometric intelligence seems to be rather unlikely. If and what specific conditions may lead to such a positive association cannot be answered from the present study but need further investigations.

Regarding the functional relationship between TRP and g, we were able to replicate previous findings. As in an increasing number of studies (e.g., [3,4,7]), TRP explained a substantial portion of variance in psychometric intelligence. More specifically, with 33% explained variance, the communality was only slightly lower than in the studies by Pahud et al. [7] with 36% or Helmbold et al. [4] with 44%. This result underscored the association between psychometric intelligence and higher timing accuracy and temporal sensitivity, as proposed by the TRP hypothesis [5].

The TRP hypothesis by Rammsayer and Brandler [5] proceeded from cognitive models proposing an internal (master) clock underlying the efficiency of information processing and transmission [56–58]. Within the framework of the TRP hypothesis, this higher efficiency is the result of faster and better coordinated information processing. Evidence for the notion that TRP leads to better coordinated mental operation was provided by Troche and Rammsayer [6], who reported that higher TRP led to higher capacity of working memory (WM), which in turn was associated with higher psychometric intelligence. It should be noted that Jastrzębski et al. [59] reported similar results but argued that WM capacity is the variable, which causes the relation between TRP and psychometric intelligence. Furthermore, the proposed positive association between mental speed and intelligence was confirmed by several studies [4,7]. In the present study, TRP was associated with SSC in the measurement model of spatial suppression. In this model, SSC reflected individual differences in speed of information processing as the time required to correctly identify the motion direction (irrespective of the spatial-suppression effect). Individuals with higher TRP needed less time to correctly identify the motion direction than individuals with lower TRP. Furthermore, the relation between SSC and psychometric intelligence decreased substantially when TRP was concurrently considered. Thus, as in previous studies [4,7], the relationship between speed of information processing (here speed of correctly detecting the motion direction) and intelligence could be explained in terms of TRP. This is particularly interesting because speed of information processing is frequently considered a major source of individual differences in psychometric intelligence [60–62]. A better understanding of the psychophysiological underpinnings of TRP in future studies might help elucidate why TRP so consistently explains the relationship between speed of information processing and psychometric intelligence.

Against our expectation, higher TRP was only weakly associated with a less (instead of a more) pronounced spatial suppression effect as reflected by the SSI latent variable. Several studies supported the idea of a more pronounced spatial-suppression effect being indicative of more efficient information processing [10,15]. Thus, these two concepts of efficiency seem to be clearly dissociable and only weakly related to each other. This weak relationship, however, was sufficient that TRP explained the complete variance shared between spatial suppression and psychometric intelligence.

In summary, consistent with the TRP hypothesis, the positive relationship between psychometric intelligence and TRP was replicated. TRP was also significantly associated with the portions of variance in MDD thresholds, which were unrelated to stimulus size (i.e., the SSC latent variable) and, thus, reflected speed of information processing. That TRP explained the common variance of this constant latent variable and psychometric intelligence corroborates the assumption that TRP underlies the relation between intelligence and speed of information processing. However, regardless of being operationalized as SI index or SSI latent variable, the spatial-suppression effect was negatively related to psychometric intelligence as well as to TRP. This contradicted the assumption of higher spatial suppression reflecting more efficient information processing [10,15]. That is, while spatial suppression is a critical mechanism for achieving efficient information processing of visual information, our results called in question prior links between spatial suppression and general brain efficiency as reflected in psychometric intelligence and TRP. If such links exist, it would be important for future research to identify the conditions under which they become effective.

Acknowledgments

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4.2 Article 2: Can the resting state peak alpha frequency explain the relationship between temporal resolution power and psychometric intelligence?

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Can the resting state peak alpha frequency explain the relationship between temporal resolution power and psychometric intelligence?

Lisa M. Makowski[1], & Stefan J. Troche[1*]
[1] Institute of Psychology, University of Bern, Bern, Switzerland

* Corresponding author at: University of Bern, Fabrikstrasse 8, 3012 Bern, Switzerland
E-mail: stefan.troche@unibe.ch (S. J. Troche)

Abstract

The temporal resolution power (TRP) hypothesis states that individuals with higher TRP, as reflected by a higher performance on several psychophysical timing tasks, perform better on intelligence tests due to their ability to process information faster and coordinate their mental operations more effectively. It is proposed that these differences in TRP are related to the rate of a master clock based on neural oscillations. The present study aimed to investigate whether the peak alpha frequency (PAF) measured via electroencephalography (EEG) reflects a psychophysiological measure of this rate and its potential role in explaining the relationship between TRP and psychometric intelligence. A sample of 129 young adults (M = 23.0, SD = 3.1) completed a short version of Raven's Advanced Progressives Matrices and three timing tasks. PAF was measured using EEG before each timing task during two resting states with eyes closed (EC) and eyes open (EO), respectively. From these PAF measurements, four latent PAF variables were extracted, differing in resting state (EC, EO) and electrode cluster (frontal/central, parietal/occipital). The results confirmed a strong association between TRP and psychometric intelligence ($r = .56$, $p < .01$), as previously reported in other studies. Additionally, we found a positive association between intelligence and a latent PAF variable extracted from frontal/central electrodes in the EO resting state conditions ($r = .27$, $p < .05$). However, there was no association between TRP and PAF. This indicates that PAF does not reflect the underlying psychophysiological mechanism that links TRP to intelligence.

Keywords: Temporal resolution power, intelligence, peak alpha frequency

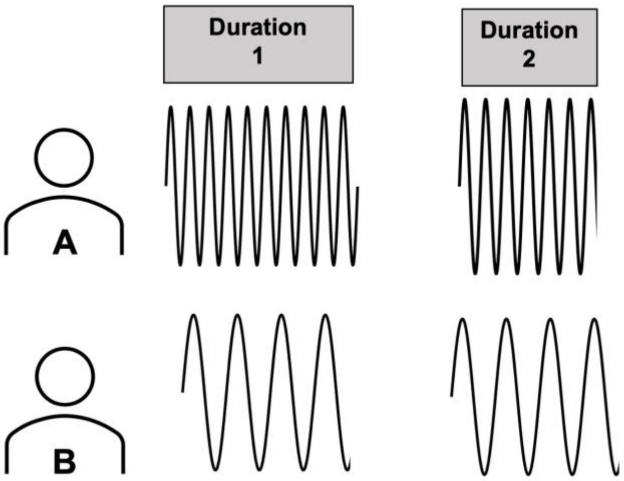
Introduction

The temporal resolution power (TRP) hypothesis holds that individual differences in the brain's timing accuracy and temporal sensitivity are basic sources of individual differences in psychometric intelligence (Rammsayer & Brandler, 2004, 2007). At a behavioral level, individual differences in TRP are measured by event-timing, interval-timing, rhythm perception, or temporal generalization tasks (Grondin, 2010; Ogden et al., 2014; van Wassenhove et al., 2019). The considerable amount of variance shared by those tasks allows for extracting a latent variable as a representation of TRP (Haldemann et al., 2012; Helmbold et al., 2007; Rammsayer & Brandler, 2004, 2007), which has repeatedly demonstrated to be functionally associated with psychometric intelligence (Haldemann et al., 2012; Helmbold et al., 2007; Makowski et al., 2022; Pahud et al., 2018; Rammsayer & Brandler, 2004, 2007; Troche & Rammsayer, 2009). Within the framework of the TRP hypothesis, Rammsayer and Brandler (2007) explain this relationship by the assumption that individuals with higher TRP process information faster and coordinate their mental operations better than individuals with lower TRP. As a result, this more efficient information processing leads to higher scores on intelligence tests (for empirical support for these assumptions, see Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b).

Proceeding from Surwillo's (1966, 1968) master clock hypothesis, Rammsayer and Brandler (2004, 2007) suggest that individual differences in neural oscillations might be the psychophysiological mechanism underlying TRP. The assumption of a single internal clock is consistent with so-called pacemaker-counter models to explain temporal judgment (for a concise review, see Grondin, 2010). According to these models, a pacemaker generates pulses registered by a counter. The number of registered pulses for a given physical time interval represents the perceived time interval (Creelman, 1962; Treisman et al., 1990; Treisman et al., 1994; Ulrich et al., 2022). Proceeding from the assumption of a pacemaker, a higher oscillatory frequency, with which the pacemaker generates pulses, allows for detecting smaller temporal differences between two stimuli or differences in their onset, which are undetectable with lower frequencies. This idea is delineated in Figure 1. An individual with a low oscillatory frequency (individual B in Figure 1) is not able to detect the temporal difference between the two stimuli since both stimuli (although physically of different duration) are associated with the same number of pulses (or oscillations) for this individual. For an individual with a higher oscillatory frequency (individual A in Figure 1), the first (and physically longer) stimulus duration is associated with a higher number of pulses than the second (and physically shorter) stimulus duration. Therefore, individual A is able to identify the first stimulus to be longer. Although the outlined mechanism is surely a simplified representation, neural oscillations are an inherent part of many cognitive models of temporal information processing (Allman et al., 2014; Grondin et al., 2010; Kononowicz & van Wassenhove, 2016; Kononowicz et al., 2018; van Wassenhove et al., 2019).

Figure 1

Illustration of the master clock based on Surwillo (1966, 1968)



The assumption that individual differences in neural oscillations underlie individual differences in TRP also provides a functional link to individual differences in psychometric intelligence, which have also been explained in terms of neural oscillations by Jensen's oscillation theory (1982, 2006). According to this theory, individual differences in excitatory and refractory states in a neuron or group of neurons lead to differences in response times (RTs) and, especially, in the intraindividual standard deviation of RTs. Thus, a higher oscillation rate leads to higher and less variable speed of information processing. With a higher speed of information processing, more information from early sensory memory can be transferred to durable memory storage so that a premature loss of relevant information can be avoided (Jensen, 1982, 2006). Furthermore, faster and more consistent processing of information in working memory prevents overloading of the capacity-limited system (and resulting response errors) when information is faster transferred to long-term memory or action so that it no longer demands working memory capacities, which can then be used for the processing of new information. With this rationale, Jensen's (1982, 2006) oscillation theory posits an explanation of the well-established link between speed of information processing and intelligence (Deary, 2001; Doebler & Scheffler, 2016; Jensen, 2006; Schubert & Frischkorn, 2020; Sheppard & Vernon, 2008). This is of particular interest since, in several studies, this link between speed of information processing and psychometric intelligence could be explained in terms of TRP (Brandler & Rammsayer, 2007; Helmbold et al., 2007; Makowski et al., 2022; Pahud et al. 2018).

Both Rammsayer and Brandler's (2007) TRP hypothesis, as well as Jensen's (1982, 2006) oscillation theory, proceed from the assumption that individual differences in neural oscillation rates are a basic mechanism underlying individual differences in psychometric intelligence. No specification of these neural oscillations, however, is made in either hypothesis. For an empirical investigation of this assumption, electroencephalography (EEG) as a method for assessing neural oscillations might be of particular interest. Traditionally, the EEG oscillations are divided into the delta, theta, alpha, beta, and gamma frequency bands (Buzsáki, 2006; Cohen, 2014; Klimesch et al., 1993). The alpha frequency band with a frequency range of 7 to 13 Hz is most prominent when the brain is in a relaxed resting state and has been functionally linked to various cognitive processes (Başar & Güntekin, 2012; Jensen & Mazaheri, 2010; Klimesch, 2012). For example, changes in alpha power during a cognitive task were found to be related to the inhibition of task-irrelevant and the activation of task-relevant brain areas (Başar & Güntekin, 2012; Klimesch, 2012). Moreover, the alpha power during a resting state prior to diverse cognitive tasks (e.g., fluid intelligence and memory tasks) was positively related to performance in these tasks (Clark et al., 2004; Doppelmayr et al., 2002; Grandy et al., 2013; Klimesch et al., 1990; Klimesch et al., 1993; Mahjoory et al., 2019).

The alpha band at rest exhibits a peak in its power spectrum. The frequency at which this peak is observed is referred to as peak alpha frequency (PAF) and shows pronounced individual differences (Hilger et al., 2022). The specific meaning of the PAF is not yet conclusively clarified. Angelakis, Lubar, Stathopoulou, and Kounios (2004) postulated that "PAF reflects cognitive preparedness, i.e., a capacity for higher-level cognitive functions, rather than lower-level functions such as arousal" (p. 896) while Klimesch (1997) assumed that "IAF reflects the speed of spreading activation and retrieval processes" (p. 329). Mierau et al. (2017) suggested "that the alpha rhythm may dictate the resolution at which information is sampled and/or processed by cortical neurons" (p. 151). Ociepka et al. (2022) found a functional positive relationship between speed of information processing on the behavioral level and PAF. They put forward the idea that individuals with higher compared to individuals with lower PAF process information faster because their optimal alpha cycle window is shorter, allowing for faster reactions. These interpretations have in common that PAF is associated with faster information processing or may even be causal for individual differences in speed of information processing.

Consistent with the above-outlined findings of a functional link between intelligence and speed of information processing, several studies reported that individuals with higher intelligence showed a higher PAF than individuals with lower intelligence (Angelakis, Lubar, & Stathopoulou, 2004; Anokhin & Vogel, 1996; Doppelmayr et al., 2002; Grandy et al., 2013; Leno et al., 2021). Hence, as a psychophysiological marker of the oscillation rate in the alpha band, the PAF might be a potential candidate for the oscillation rate underlying individual differences in psychometric intelligence as proposed by Jensen (2006) or Rammsayer and Brandler (2007). However, other studies failed to replicate this association (Finnigan & Robertson, 2011; Ociepka et al., 2022; Pahor & Jaušovec, 2016; Posthuma et al., 2001). Thus, although there is some empirical evidence for the notion that PAF relates to individual differences in psychometric intelligence, the pattern of results is rather inconsistent (see also Hilger et al., 2022).

To the best of our knowledge, no study has investigated the potential link between PAF and TRP as a latent variable representing timing accuracy and temporal sensitivity in a general, task-unspecific way. A few studies, however, have examined the relationship between temporal information processing in specific timing tasks and PAF. In these studies, PAF was not systematically related to the performance on a duration discrimination task (Milton & Pleydell-Pearce, 2017) nor to the performance on a temporal estimation task (Venskus & Hughes, 2021). Also Glicksohn et al. (2009) could not find a significant association between PAF measured at rest and performance in a temporal production task. However, when they differentiated PAF from the right and the left hemisphere and regressed both on the produced duration, a substantial amount of individual differences in the produced duration could be explained, indicating a suppression effect of right and left PAF. Additionally, Samaha and Postle (2015) reported that two-flash fusion thresholds measuring temporal resolution in the visual system were smaller in individuals with higher compared to individuals with lower PAF (Samaha & Postle, 2015). Thus, there is some evidence for a functional association between temporal information processing and PAF, but the pattern of empirical results is as inconsistent as the results on the relationship between psychometric intelligence and PAF.

There are several explanations for the inconsistencies in previous studies on the relationship between PAF and psychometric intelligence, as well as between PAF and temporal information processing. The first reason refers to the specificities of the PAF measurement, such as the type of resting state in which PAF was measured. For example, in some studies PAF was measured during an eyes-closed (EC) resting state (Anokhin & Vogel, 1996; Finnigan & Robertson, 2011; Glicksohn et al., 2009; Pahor & Jaušovec, 2016; Posthuma et al., 2001; Samaha & Postle, 2015) and, in others, during an eyes-open (EO) resting state (Leno et al., 2021; Ociepka et al., 2022). In another study, PAF was calculated as a difference score between EC and EO resting states (Trammell et al., 2017). Only a few studies considered the PAF from EC and EO resting states separately (Angelakis, Lubar, & Stathopoulou, 2004; Angelakis, Lubar, Stathopoulou, & Kounios, 2004; Grandy et al., 2013).

Furthermore, studies also differed in the electrode sites, at which PAF was measured. Most studies used parietal and occipital electrodes (Glicksohn et al., 2009; Grandy et al., 2013; Milton & Pleydell-Pearce, 2017; Posthuma et al., 2001; Samaha & Postle, 2015; Trammell et al., 2017; Venskus & Hughes, 2021), where the alpha rhythm is more pronounced than under more anterior electrodes in the resting state (Klimesch, 1999). Other studies averaged the PAF from electrodes across the entire scalp (Angelakis, Lubar, & Stathopoulou, 2004) or used occipital electrodes in one subset of participants and frontal electrodes in another subset of participants (Ociepka et al., 2022). Only a few studies distinguished between the different recording sites, e.g., between frontal and parietal electrodes (Anokhin & Vogel, 1996; Doppelmayr et al., 2002; Finnigan & Robertson, 2011; Pahor & Jaušovec, 2016).

A further reason for inconsistencies in studies on the relationship between PAF and psychometric intelligence, as well as between PAF and temporal information processing, might be seen in using only a single measure of PAF or the average of two measurements. PAF measures are not perfectly reliable (Ghazi et al., 2021), and PAF variance is not only affected by trait differences between individuals but also by (unstable) state differences (Angelakis, Lubar, & Stathopoulou, 2004; Angelakis, Lubar, Stathopoulou, & Kounios, 2004; Haegens et al., 2014; Mierau et al., 2017). Therefore, single measurements can be expected to be biased estimations of interindividual differences in the trait-related (or cross-situational) mechanisms underlying PAF. A possible solution to this challenge might be to measure PAF repeatedly to extract a latent variable as an error-free and situation-independent measure of PAF.

The main goal of the present study was to investigate the assumption that individual differences in neural oscillations underlie TRP and its relation to psychometric intelligence (Rammsayer & Brandler, 2007). More specifically, we aimed to investigate whether PAF represents individual differences in the neural oscillation rates underlying both psychometric intelligence and TRP. Thus, we expected a mediating effect of PAF on the relationship between TRP and psychometric intelligence. In order to represent PAF at a latent level, PAF was assessed six times, i.e., during an EC and an EO resting state before each of the three timing tasks. Since we used 64 electrode sites for the EEG, we also addressed the question of whether PAF during EC or EO resting states and at different clusters of electrode sites differentially relates to psychometric intelligence, TRP, and their relationship.

Methods

Participants

Participants were 172 volunteers recruited via the student platform of the University of Bern, online advertisements, and the personal environment of the investigators. Of this sample, 26 participants had to be excluded due to a high number of artifacts in their EEG (less than 20% of segments available for further analyses), six due to univariate (exceeding the group mean by three standard deviations in their performance measures), and eleven due to multivariate outlier analyses on their behavioral performance. This resulted in a final sample of 129 participants (93 female, 36 male) aged 18 to 34 years ($M_{age} = 23.0$; $SD = 3.1$ years). This surprisingly high number of participants to be excluded may be because the study was conducted during the COVID-19 pandemic, so the investigator and participants were obliged to wear a medical mask during the whole measurement. The mask in combination with the electrode cap was uncomfortable for many participants, which led to more movements, muscle tension and itching reflected in more EEG artifacts than usually observed in our laboratory.

Only right-handed (according to the Edinburgh Handedness Scale; Oldfield, 1971) and healthy participants took part in the study. Thus, participants who reported in a survey to suffer from a psychological disease, a chronic disease, or with a cardiac and neuronal history (e.g., cranium brain trauma), or taking medications, did not participate in this study. All participants showed normal or corrected-to-normal vision and no auditory impairments, which was ensured by the performance of an audiometry task. Regarding their highest education, 11% of the participants had finished vocational school, and 89% had higher educational training.

For their participation, they received either 30 Swiss francs, course credits, or could participate in a price draw of vouchers. All participants signed written informed consent before their participation. The study was approved by the local ethics committee of the Faculty of Human Sciences of the University of Bern (No. 2020-08-00001).

Measurement of psychometric intelligence

For the measurement of intelligence, participants completed a short version of the Advanced Matrices Test (APM; Raven et al., 1998). The adapted version consisted of the 18 odd-numbered APM items proposed by Sefcek et al. (2016), who reported an internal consistency of $\alpha = .79$. The APM was presented on a Dell monitor of 22 inches with a resolution of 1680 x 1050 (32 bits/pixel) and a refreshing rate of 60 Hz. Participants gave their responses on an HP computer keyboard and were given a time limit of 20 minutes for the 18 items.

Assessment of temporal resolution power

Temporal resolution power was assessed with three timing tasks. The tasks were programmed with Eprime 2.0 (Psychology Software Tools, 2012). Auditory stimuli were presented via ER3C® tubal insert earphones (Etymotic Research Inc., 2022) at an intensity of 70 dB. Visual information was presented on the same monitor as the APM. Participants were seated 70 cm from the monitor and gave their answers by clicking on a designated key on a Chronos® response box (Psychology Software Tools, 2012).

Temporal order judgment (TOJ) task

The TOJ task consisted of 64 trials in which a visual and an auditory stimulus were presented. The auditory stimulus was a 1000 Hz sinusoidal tone, and the visual stimulus was a green LED light centered above the computer screen. In 32 trials, the tone started after the light turned on. In the other 32 trials, the onset of the light occurred after the onset of the tone. Both stimuli ended simultaneously 200 ms after the onset of the second stimulus. In the first trial of both series, light and tone were presented with a stimulus onset asynchrony (SOA) of 70 ms. After each trial, participants had to decide whether the light or the tone occurred first by pressing one of two correspondingly labeled response keys. The SOA duration for the next trial varied depending on the participant's response accuracy using the weighted up-down procedure (Kaernbach, 1991), which settled at 75% correct responses. A correct response led to a decrease in SOA, and an incorrect response led to an increase in SOA in the next trial of the respective series. Both series were interleaved and presented randomly, with trials separated by an intertrial interval of 1500 ms.

As a measure of performance, the mean SOA was computed for the last 20 trials of each series and the two scores were averaged into one score. The mean SOA represents the 75%-TOJ threshold with lower values indicating better performance. For further analyses, the values of the mean 75%-TOJ threshold were reversed so that higher values indicate better performance. In a previous study, this TOJ task showed a retest reliability of $r_{tt} = .73$ (Rammsayer & Brandler, 2002).

Temporal generalization (TG) task

The TG task was embedded in a dissociation paradigm, which allowed for assessing temporal and pitch generalization (PG) with the same stimulus material. Since temporal but not pitch discrimination was relevant for the present study, we refer only to the TG part of the task. The TG task consisted of 108 trials. At the beginning of the task, participants were introduced to a standard tone (1000 Hz, 1000 ms) and had to memorize its duration by listening at least five times to this tone. Afterward, the experimental phase began, and participants were randomly presented either with the standard duration (1000 ms) or with an alternative duration (925 ms, 950 ms, 975 ms, 1025 ms, 1050 ms, or 1075 ms). After each stimulus presentation, they had to decide whether the stimulus was the standard by pressing designated keys with "Yes" or "No" on the Chronos® response box. After their response, they received visual feedback ('+' indicated a correct answer, '–' a wrong answer) on the monitor center for 1500 ms, followed by an intertrial interval of 900 ms. The standard duration was presented 54 times, and each alternative duration was presented 18 times. Since it was a dissociation paradigm, the presented tones did not only differ in their duration but also in their pitch (970 Hz, 980 Hz, 990 Hz, 1000 Hz, 1010 Hz, 1020 Hz, 1030 Hz; see also Gibbons et al., 2003), which should not be attended in the TG part. In the second part of the experiment, the PG task was presented with the same stimuli, but participants should ignore the duration of the stimuli and attend to their pitch.

As a performance measure, the index of response dispersion (IRD) was calculated by dividing the relative frequency of "Yes" responses to the standard duration by the total relative frequencies of "Yes" responses to all seven stimulus durations (McCormack et al., 1999). IRD values vary between 0 and 1, with a value of 1 indicating that all the "Yes" answers were given in response to the standard and not to the alternative durations.

Duration discrimination (DD) task

A standard sinusoid 1000 Hz tone with a duration of 1000 ms and a comparison tone (1000 Hz, sinusoid tone) varying in duration were presented in each trial with a 900 ms interstimulus interval. The task consisted of 64 trials, with the comparison interval being shorter than the standard interval in 32 trials and the comparison interval being longer than the standard interval in the other 32 trials. The trials of the two series were interleaved, and the order of standard and comparison intervals was randomized. Participants had to indicate whether the first or the second interval was longer for each trial by pressing a designated key. After an intertrial interval of 1500 ms, the subsequent trial started.

The duration of the comparison interval varied according to the adaptive weighted-up-down procedure (Kaernbach, 1991). Accordingly, an incorrect response in the first six trials led to a prolongation of the comparison interval by 9 ms compared to the standard interval. In contrast, a correct response resulted in a decrease of 3 ms. This procedure changed for the seventh to 32nd trial, where the increase after an incorrect response was 6 ms, and the decrease after a correct response was 2 ms. This procedure resulted in two thresholds, the 25%-difference threshold for the series with the comparison being shorter than the standard interval and the 75%-difference threshold for the series with the comparison being longer than the standard interval. For each threshold, the comparison intervals in the last twenty trials of the respective series were averaged. Then, the difference threshold (DL) was calculated by dividing half of the interquartile range [(x.75-x.25)/2], with better performance indicated by smaller values (Luce & Galanter, 1963). As for the TOJ task, the DL values of the DD task were reversed for further analyses so that larger values indicated better performance. In a previous study, the DD task showed a retest-reliability of $r_{tt} = .75$ (Lapid et al., 2008).

EEG recording and preprocessing

Prior to each timing task, the EEG was recorded during a 60-seconds EC and, afterward, a 60-seconds EO resting state during which participants were asked to fix their gaze on a white cross presented in the center of a black monitor screen. For the EEG recording, a 64-channel Biosemi ActiveTwo EEG system (Biosemi, 2022) was used with active gel electrodes and a sampling rate of 2048 Hz. Horizontal and vertical electrooculogram (EOG) was recorded with electrodes at the outer canthi of the right and left eye (horizontal), the Fp1 electrode, and an electrode under the left eye (vertical). Two additional flat-type active electrodes were adjusted on the mastoids and later served as reference electrodes. During recordings, the offset of the active electrodes was kept below 35 μV, and the CMS and DRL sites served as online ground electrodes (see Biosemi, 2022). The EEG recordings were offline preprocessed in Brain Vision Analyzer 2.2 (Version 2.2.1.8266; Brain Products, 2019). Data were re-referenced to the average of the two mastoids. The sampling rate was adjusted from 2048 Hz to 1024 Hz. Impulse response filters were applied with a notch filter at 50 Hz and a high-pass filter at 0.1 Hz (Order 2, time constant [s] = 1.59). Eye movement artifacts were corrected using the ocular correction by Gratton and Coles (1989). Then, the electrodes Fp1, Fpz, Fp2, AF3, AF4, AFz, AF7, and AF8 were excluded to reduce the number of trials with ocular artifacts, which were most pronounced at these electrode sites. Muscular artifacts were frequently found at electrodes P1, P2, and Iz, which were therefore also discarded. This resulted in 53 remaining electrodes. Bad channels (e.g., channels with no or noisy signal during a resting state) were interpolated using spherical spline interpolation of the neighboring channels (Perrin et al., 1989). Afterward, additional artifacts were excluded with a semiautomatic raw data inspection with the following presettings: maximal allowed voltage step of 50 µV/ms, the minimal allowed amplitude of -100 µV, and the maximally allowed amplitude of 100 µV. The artifacts marked by this algorithm were all checked manually afterward. Then the data was segmented by dividing each EC and EO resting state into 60 two-second epochs with 50% overlap. A semiautomatic artifact rejection was conducted with the following presettings: a maximal allowed voltage of 50 µV/ms, a maximal allowed difference of values in intervals of 200 µV, and lowest allowed activity in intervals of 0.5 µV. As with the raw data inspection, all artifacts marked by the algorithm were checked manually afterward. In total, the raw data inspection and artifact rejection analysis led on average to 16% (± 7%) and 14% (± 7%) discarded segments in the EC and the EO resting state condition, respectively

For the PAF extraction, an FFT with a 10% Hanning window was performed with a resolution of 0.50 Hz. Then, the two second segments were averaged separately for EC and EO resting states. Afterward, the PAF was determined as the frequency between 7 and 13 Hz with the highest power for each electrode in each EC and EO resting state before each timing task. The PAF information was then exported for further analyses in Hz.

Time course of the study

For the first part of the study, participants completed an online questionnaire at home via Qualtrics (Qualtrics, Provo, UT) in which they were asked about their demographics, handedness, and health status. For the second part, the study took place in a soundproof examination booth, protected from sound and electromagnetic radiation. The session started with the audiometry task, followed by the set-up of the EEG. Then, the APM was administered, followed by the TOJ task, the TG task, and finally, the DD task. All tasks were always presented in the same order. The entire session lasted between two and a half to three hours per participant. Between the tasks, participants were always offered a break.

Statistical data analysis

The statistical analyses were conducted with the programs R (Version 4.1.0; R Core Team, 2021) and R-Studio (Version 1.4.1106; RStudio Team, 2021) using the following packages: the GPArotation package (Bernaards & Jennrich, 2005), the Hmisc package

(Harrell Jr, 2021), the lavaan package (Rosseel, 2012), the psych package (Revelle, 2022) and the rstatix package (Kassambra, 2022). All performance measures were z-standardized for further statistical analyses. Then, descriptive statistics and correlations were computed, followed by three exploratory factor analyses (EFA) – one for the PAF measurements prior to each of the three timing tasks (at 53 electrode sites during the EC and the EO resting state). The aim of the EFA was to identify more or less homogeneous clusters of electrode sites for the PAF measures and to test whether PAF measures during the EC and EO resting states should be treated separately or not. Scree plots with parallel analyses were created with ggplot2 (Wickham, 2016) and ggpubr (Kassambra, 2022) based on the code of Sakaluk and Short (2016). From the PAF factors revealed by means of EFA, a measurement model for PAF was developed by means of confirmatory factor analyses (CFA) to represent an appropriate number of latent variables representing PAF.

Two further CFA were conducted to investigate the latent relationship between psychometric intelligence and TRP. Since intelligence was only measured with one task, we built three parcels from the APM items, with parcel 1 containing items 1, 4, 7, 10, 13, and 16, parcel 2 containing items 2, 5, 8, 11, 14, and 17, and parcel 3 containing the items 3, 6, 9, 12, 15, and 18. From the sum scores of the three parcels, a latent variable was extracted to represent psychometric intelligence. A second latent variable was derived from the performance scores on the three timing tasks. Then, the latent TRP-intelligence relationship was analyzed by means of structural equation modeling (SEM), and finally, the PAF measurement model was added to this model to test the assumption that the relation between TRP and psychometric intelligence would be mediated by PAF.

All CFA and SEM were estimated with robust maximum likelihood estimation. Model fit was evaluated by means of χ^2 values, comparative fit index (CFI), root mean square error of approximation (RMSEA), and standardized root means squared residual (SRMR). Good (acceptable) fit was indicated by $\chi^2/df < 2$ (Schermelleh-Engel et al., 2003), CFI $\geq .95$ ($\geq .90$), RMSEA $\leq .05$ ($\leq .08$), and SRMR value $\leq .08$ ($\leq .10$) (Schweizer, 2010). The data is available in the BORIS database at https://doi.org/10.48620/270.

Results

Behavioral data

Descriptive statistics and correlations

The descriptive statistics of and correlations between performance measures from the APM, DD, TOJ, and TG tasks can be seen in Table 1. All correlation coefficients were small but statistically significant and in a similar range as in previous studies (see Haldemann et al., 2012).

Table 1

Descriptive statistics and Pearson correlations of the behavioral performance measures from the three timing tasks and APM.

Performance measures	*M*	*SD*	Min	Max	Skewness	Kurtosis	Pearson correlations		
							1.	2.	3.
1. APM [sum score]	13.03	2.61	5	18	-0.50	-0.01	–		
2. TOJ [threshold in ms]	134	29	56	198	-0.22	-0.19	.22*		
3. TG [IRD]	0.15	0.02	0.09	0.22	0.26	0.25	.21*	.25**	
4. DD [DL in ms]	134	42	43	252	0.60	-0.12	.25**	.25**	.21*

Note. $N = 129$. APM = sum score from the short version of Raven's Advanced Progressive Matrices. TOJ = mean 75%-difference threshold from the temporal order judgment task. TG = index of response dispersion (IRD) from the temporal generalization task. DD = difference limen (DL) from the duration discrimination task. For the Pearson correlations, the performance measures of the TOJ and DD task were reversed. * $p < .05$, ** $p < .01$

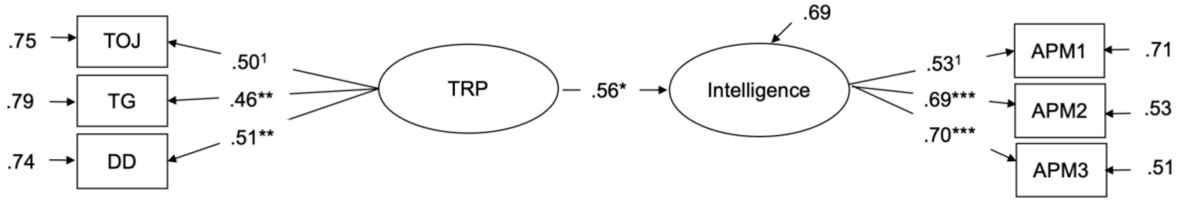
Measurement and latent regression models for APM and TRP

The three parcels from the 18 APM items correlated significantly with each other ranging from $r = .35$ to $r = .48$, all *p*s < .001. These substantial correlations allowed for extracting a latent variable from these parcels by means of CFA, representing a proxy of psychometric intelligence with a McDonald's omega coefficient of $\omega = 0.68$. Due to only three manifest variables, the model was exactly identified (Kline, 2011). Analogously, a latent variable, referred to as temporal resolution power ($\omega = 0.49$), was derived from the three different timing tasks, which also correlated significantly with each other (see Table 1).

The above-described measurement models were combined in a latent regression model to test the TRP hypothesis. The resulting model is presented in Figure 2 and showed a good model fit, SB$\chi^2(8) = 2.515$, $p = .961$, $\chi^2/df = 0.314$, CFI = 1.000, RMSEA = .000, SRMR = .022. The regression coefficient from TRP to psychometric intelligence was significant $\beta = .56$, $p = .021$. The shared variance of about 31% between TRP and psychometric intelligence established the link, which we aimed to explain by PAF in the present study.

Figure 2

*Structural equation model of the relationship between temporal resolution power (TRP) and psychometric intelligence. *p < .05, **p < .01, ***p < .001*



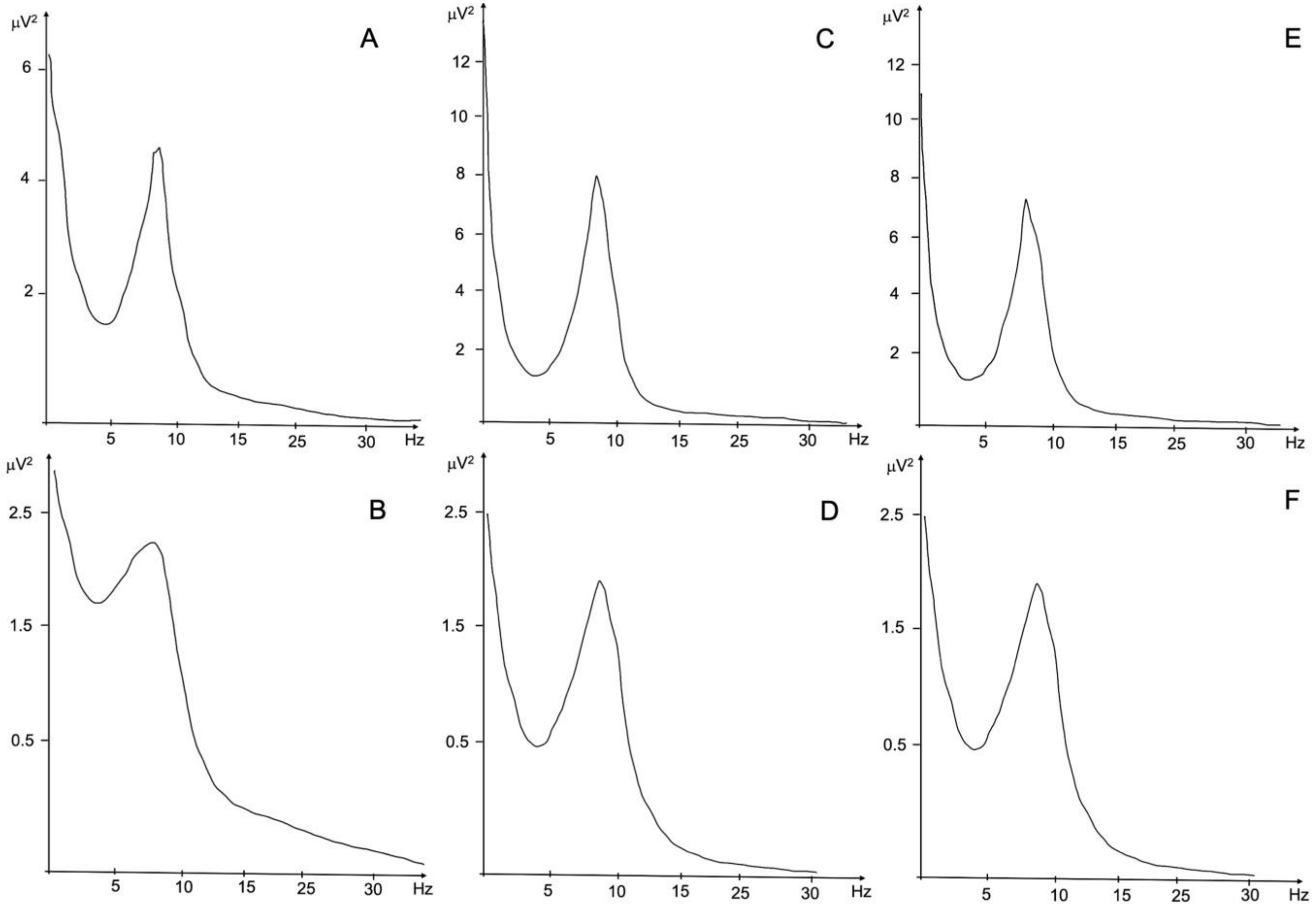
Electrophysiological data

Descriptive statistics and correlations

As displayed in Figure 3, PAF varied between 7.00 and 12.50 across the EC and EO resting states before the three timing tasks. PAF was measured with 64 electrodes twice immediately before each timing task - once EO, once EC. Of these 64 electrodes, 11 electrodes had to be removed (for further information, see methods section).

Figure 3

The mean power spectrum measured during the EC (A) and EO resting state (B) before the TOJ task, during the EC (C) and EO resting state (D) before the TG task, as well as during the EC (E) and EO resting state (F) before the DD task based on 53 electrodes (N = 129).



Note. The peak between 7 to 13 Hz represents the peak alpha frequency.

Exploratory factor analyses

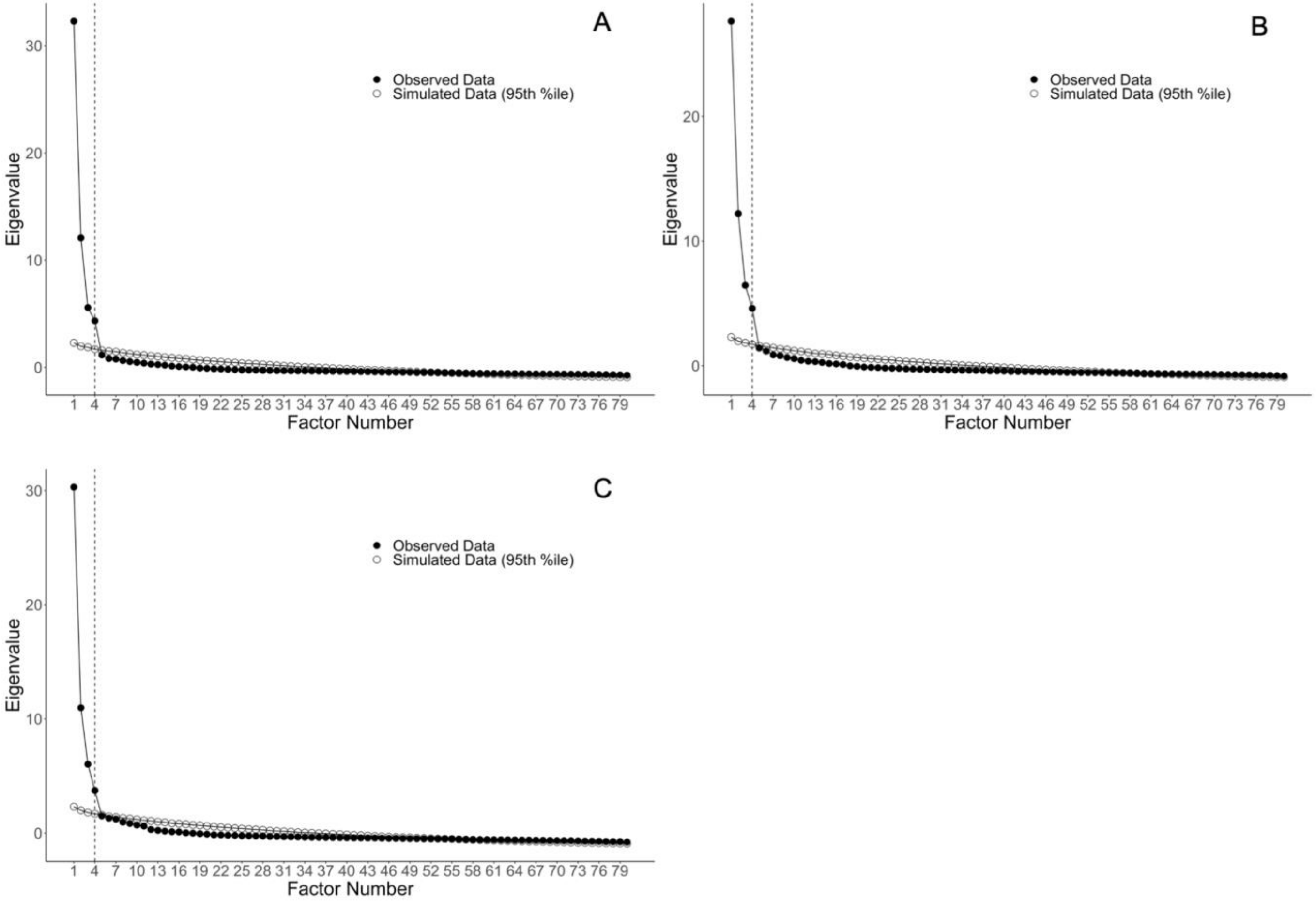
To test whether the 2 x 53 PAF measures before each of the three tasks could be reduced consistently to fewer factors, three exploratory factor analyses (EFAs) were conducted. In all three EFAs, we found evidence for four underlying factors: Two of these four factors represented measures from the EO, and the other two factors represented measures from the EC condition. Furthermore, the two EO and the two EC factors represented frontal/central (FC) and parietal/occipital (PO) electrode sites, respectively. These factors are referred to below as EO-FC, EO-PO, EC-FC, and EC-PO factors. To note, no separate factors for right and left electrodes emerged in the exploratory factor analyses. When factors for the two hemispheres were extracted anyway, multicollinearity resulted from high correlations between the right and left electrodes from the same time point (EC, EO) and corresponding electrode sites (e.g., frontal/central). Therefore, the separate influence of right and left electrodes investigated in the study by Glicksohn et al. (2009) could not be examined with the present data.

As presented in more detail in the supplemental material, this pattern of results was rather clear for the TG task (see Table S1), while a fifth factor emerged in the PAF data measured before the DD (see Table S2), and a fifth and sixth in the PAF data measured before the TOJ task (see Table S4). The fifth factor in the measures before the DD task seemed to be an artifact, as it could not be assigned to any coherent cluster of electrodes (see details in the supplemental material). Before the TOJ task, the fifth factor referred to central and centro-parietal electrodes (C and CP) during EC, whereas the sixth factor referred to central and temporal (C, T, TP) electrodes during EO. Also, in the other two EFAs, the CP electrodes, as well as FT7, FT8, T7, T8, TP7, and TP8, could not be assigned unambiguously to a factor.

Therefore, we excluded thirteen electrodes that could not be clearly assigned to frontal/central or parietal/occipital areas (CP1, CP2, CP3, CP4, CP5, CP6, CPz, TP7, TP8, T7, T8, FT7, and FT8) before we repeated the three EFAs. In all three EFAs, the parallel analysis suggested now four factors for the PAF measures before each task (see Figure 4).

Figure 4

Scree plots with parallel analysis of the PAF values measured before the TG task (A), before the DD task (B), and before the TOJ task (C)



Note. In each EFA, PAF measurements from 40 electrodes during the resting state with eyes closed and during the resting state with eyes open were submitted.

In all three EFAs, an EO-FC, an EO-PO, an EC-FC, and an EC-PO factor could be derived from the same set of electrodes (see Tables S5-S7 in the supplemental material). Some electrodes still had substantial secondary loadings (> .30) on another factor. Still, the differences between the primary and the secondary factor loadings were so large that the corresponding assignment to the respective factor was justified. There were only a few exceptions: One was the PAF measure under the Oz electrode during the EO condition before the DD task, which loaded similarly strongly on the EO-PO and the EC-PO factor (see Table S6). More critically, the PAF measures under the electrodes C3 to C6 and FC6 in the EO condition before the TOJ task loaded more strongly on the EO-PO factor than on the EO-FC factor, but the factor loadings on the EO-FC factor were also statistically significant, except for C4 and C5 (see Table S7). Thus, across all resting states before the three timing tasks, a consistent factorial PAF pattern could be obtained by means of EFA with separable factors for the EC and EO conditions and separable factors describing frontal/central and parietal/occipital PAF.

For each of the twelve factors (four factors for the measurements before each of the three tasks), factor scores were extracted. Their intercorrelations and correlations with behavioral performance measures from the APM and the three timing tasks are presented in Table 2. PAF factor scores were positively and significantly correlated, with only a few exceptions when they were based on different electrode clusters and different resting states. Performance in the APM was positively associated with the EO-FC factor when measured before the TG task indicating that higher APM scores came along with higher PAF at frontal/central electrodes in the EO resting state before the TG task. For the timing tasks, only the index of dispersion from the TG task was positively associated with two PAF factor scores, namely with the EO-PO factor scores when measured prior to the DD and prior to the TOJ task, suggesting that higher PAF values (measured during eyes open before the DD and before the TOJ at parietal/occipital electrodes) were associated with better performance in the TG task. The significant coefficients should be interpreted cautiously because alpha inflation was not corrected for the number of 120 correlations in Table 2.

Table 2

Pearson correlations between intelligence (APM), timing tasks (DD, TG, TOJ), and the PAF factor scores.

Measures	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. APM	–														
2. TOJ	.22*														
3. TG	.21*	.25**													
4. DD	.25**	.25**	.21*												
5. PAF – TOJ (EC-FC)	.01	-.01	.00	-.12											
6. PAF – TOJ (EC PO)	-.11	-.10	-.11	-.02	.41***										
7. PAF – TG (EC-FC)	.05	.02	.02	-.05	.83***	.48***									
8. PAF – TG (EC-PO)	-.01	.02	.02	.03	.40***	.84***	.52***								
9. PAF – DD (EC-FC)	.05	-.07	.01	-.06	.78***	.35***	.77***	.31***							
10. PAF – DD (EC-PO)	-.09	-.01	-.01	.03	.38***	.86***	.48***	.83***	.39***						
11. PAF – TOJ (EO-FC)	.12	.01	.11	.02	.32***	.05	.32***	.06	.29**	.07					
12. PAF – TOJ (EO-PO)	.16	.01	.19*	.07	.40***	.33***	.52***	.38***	.39***	.39***	.45***				
13. PAF – TG (EO-FC)	.18*	.12	.04	.03	.39***	.05	.35***	.10	.26**	.14	.67***	.43***			
14. PAF – TG (EO-PO)	.12	-.02	.16	.09	.45***	.20*	.40***	.29**	.35***	.28**	.32***	.71***	.38***		
15. PAF – DD (EO-FC)	.14	.12	.05	.01	.41***	.00	.29***	-.01	.33***	.01	.60***	.37***	.69***	.40***	
16. PAF – DD (EO-PO)	.09	-.05	.25**	.11	.34***	.14	.28**	.11	.35***	.23**	.39***	.67***	.30***	.65***	.34***

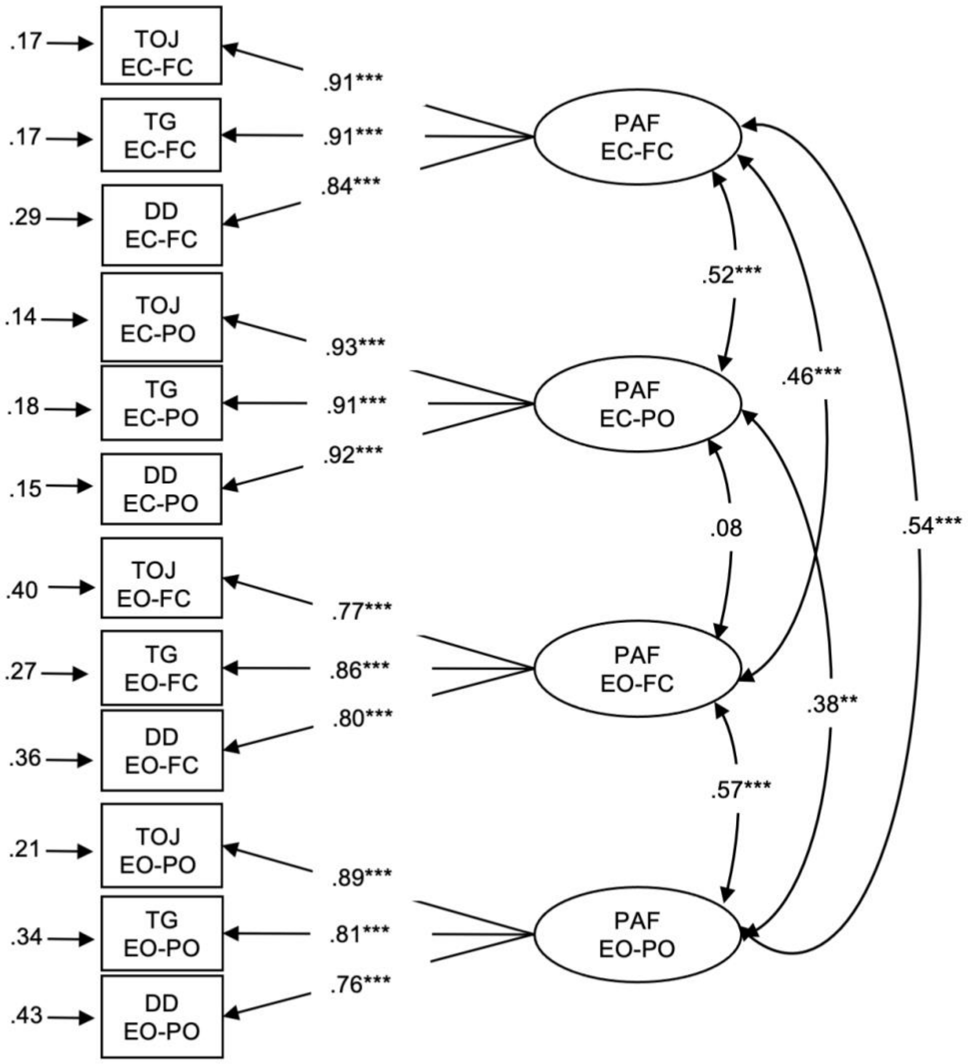
Note. *N* = 129. APM = short version of Raven's Advanced Progressive Matrices, DD = Duration discrimination task, TG = Temporal generalization task, TOJ = Temporal order judgment task, variable 5 to 10 represents the PAF factor scores extracted from parietal/occipital electrodes (PO) and frontal/central electrodes (FC) during eyes closed (EC), variable 11 to 16 represents the PAF factor scores extracted from PO and FC during eyes open (EO), before each timing task (DD, TG, TOJ). * $p < .05$, ** $p < .01$, *** $p < .001$

PAF model

Given the similar factorial pattern of the PAF measures before the three timing tasks, the three EC-FC factors, the three EC-PO factors, the three EO-FC factors, and the three EO-PO factors might be further reduced to four second-order factors. To test this assumption, a CFA was conducted with a second-order EC-FC factor ($\omega = 0.92$), a second-order EC-PO factor ($\omega = 0.94$), a second-order EO-FC factor ($\omega = 0.85$), and a second-order EO-PO factor ($\omega = 0.86$) from the factor scores of the 12 PAF factors. This four-factor model, depicted in Figure 5, had an acceptable to good fit, SB$\chi^2(48) = 82.819$, $p = .001$, $\chi^2/\text{df} = 1.725$, CFI = .957, RMSEA = .075, SRMR = .045. As shown in Figure 5, all correlations between the four latent variables in the four-factor model were positive and statistically significant except for the correlation between the EC-PO and the EO-FC latent variables, $r = .08$, $p = .473$. This was probably the reason why a further reduction of the latent variables to a single higher-order PAF latent variable led to a bad model fit, SB$\chi^2(50) = 99.112$, $p < .001$, $\chi^2/\text{df} = 1.982$, CFI = .939, RMSEA = .087, and SRMR = .086, which was also significantly worse compared to the model fit of the four-factor model as indicated by a significant χ^2-difference test, $\Delta\chi^2(2) = 43.160$, $p < .001$, and by a higher AIC ($\text{AIC}_{\text{4factors}} = 3330.667$; $\text{AIC}_{\text{hierarchical}} = 3347.125$).

Figure 5

The four-factor CFA model of PAF variables measured during resting state (EC, EO) before three timing tasks (TOJ, TG, DD). ** $p < .01$, *** $p < .001$



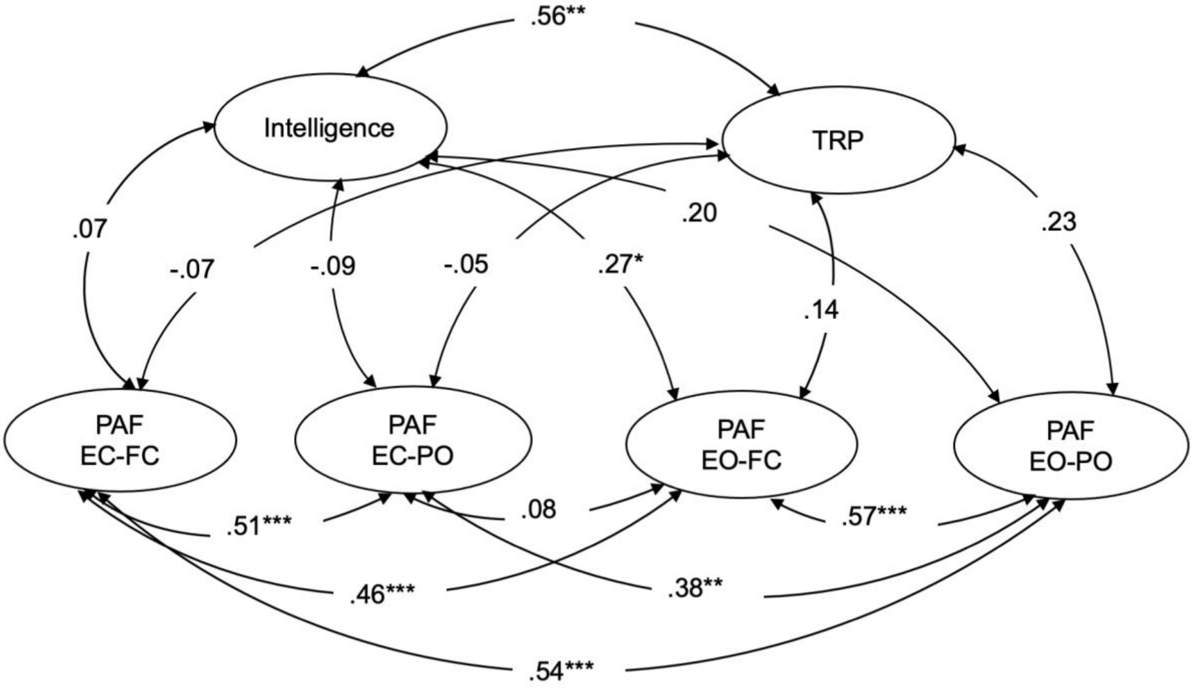
Association between intelligence, TRP, and PAF

To investigate the interplay among intelligence, TRP, and PAF, the measurement models of the APM, TRP, and PAF were combined, and correlations between APM, TRP, and the four PAF latent variables were freely estimated. The core of the model is presented in Figure 6 and had a good fit, $SB\chi^2(120) = 160.709$, $p = .008$, $\chi^2/df = 1.339$, CFI = .960, RMSEA = .051, SRMR = .050. Intelligence was significantly positively associated with TRP ($r = .561$, $p = .004$), indicating that higher intelligence was associated with higher TRP. Moreover, intelligence was also significantly positively correlated with the EO-FC latent PAF variable ($r = .27$, $p = .023$). However, no other latent PAF variable correlated significantly with intelligence. More critically, TRP was not systematically related to any of the four latent

PAF variables. It should be noted that neither the correlations between intelligence and latent PAF variables nor between TRP and latent PAF variables changed substantially when TRP or intelligence were excluded, respectively.

Figure 6

*The core of the structural equation model with freely estimated correlations to investigate the interplay between the six latent variables intelligence, temporal resolution power (TRP), and the four latent PAF variables (PAF EC-FC, PAF EC-PO, PAF EO-FC, PAF EO-PO). * p < .05, ** p < .01, *** p < .001*



In a next step, a parallel mediation analysis with four mediators (PAF variables) was specified, which led to a good (acceptable) fit with SBχ^2(120) = 160.709, $p = .008$, χ^2/df = 1.339, CFI = .960, RMSEA = .051, SRMR = .050. As can be seen in the supplemental material, the model yielded only a significant direct and total effect from TRP on intelligence but no significant indirect effect mediated by a latent PAF variable. A bootstrapping procedure revealed that all 95% confidence intervals of the indirect effects included 0, while the direct and total effects remained significant. Thus, we could not obtain evidence for the notion that the TRP-intelligence link was mediated by PAF.

Discussion

The present study examined whether individual differences in PAF underlie TRP and its relationship to psychometric intelligence (Rammsayer & Brandler, 2004, 2007; Surwillo, 1966, 1968). As a confirmation of the TRP hypothesis, TRP explained 31% of the variance in intelligence, which was similar to previous findings (e.g., 33% in Makowski et al., 2022 or 36% in Pahud et al., 2018). Furthermore, the PAF measures could be reduced to four factors per measurement time point (EC frontal/central, EC parietal/occipital, EO frontal/central, EO parietal/occipital) by means of exploratory factor analyses. Intelligence was positively associated with PAF measured at frontal/central electrodes during the EO resting state before the TG task. PAF measured at the parietal/occipital electrodes before the DD task and before the TOJ task was positively associated with the index of dispersion derived from the TG task. At the higher-order latent level, where the twelve PAF measures were reduced to four latent variables across the three tasks, intelligence was associated with PAF at frontal/central electrodes in the EO condition, while TRP was not related to any PAF variable. Thus, the present study could not confirm the assumption of individual differences in PAF underlying TRP and its relationship to psychometric intelligence.

A major challenge in the present study was the selection of the type of resting state (EO vs. EC) and the selection of the relevant electrodes for the PAF measurement. This was due to a lack of guidelines or rules for these choices. Previous studies on the link between PAF and intelligence, as well as the link between PAF and temporal information processing severely differ in their electrode selection and choice of EO and/or EC resting states. Here, we measured PAF in EC *and* EO resting states and across the whole scalp before each timing task. To identify dissociable electrode clusters for the PAF, we used exploratory factor analyses and identified highly similar clusters across the three measurement time points (i.e., before each timing task) with a differentiation between frontal/central and parietal/occipital electrodes in the EO and the EC conditions, respectively. Electrodes on the border between these clusters (mainly from the CP line) could not be assigned unambiguously to the frontal/central or the parietal/occipital clusters, so they were excluded. Our results indicate that investigations of individual differences in PAF should differentiate between frontal/central and parietal/occipital electrodes and should not treat measures from EC and EO resting states as interchangeable. The fact that we found four highly similar PAF factors during the two resting states before each of the three timing tasks did not only point to the consistency of this pattern of results but also allowed for the extraction of higher-order latent variables for the further investigation of the links between PAF and psychometric intelligence as well as temporal information processing.

According to Jensen's oscillation theory (1982, 2006), individuals with faster neural oscillations process information faster and with less variability, which should lead to better performance on intelligence tests. PAF is a promising measure to probe Jensen's assumption since it is defined as a general measure of information processing speed (Drewes et al., 2022; Grandy et al., 2013; Hilger et al., 2022; Ociepka et al., 2022). In the present study, only one of the twelve PAF measures extracted from exploratory factor analyses was significantly but weakly related to psychometric intelligence. This measure referred to PAF at frontal/central electrodes in the EO condition before the TG task. In the parallel measures (i.e., PAF at frontal/central electrodes in the EO condition before the DD and before the TOJ task), the correlations were not statistically significant, but they were positive and not significantly smaller than in the EO condition before the TG task (see Table 2). It is probably a consequence of this pattern of results that a higher-order latent variable representing PAF at frontal/central electrode sites across the three EO measures was substantially and positively associated with psychometric intelligence when situation-specific variance was discarded from the higher-order latent variable (see Figure 6).

Strikingly, our finding of a functional link between psychometric intelligence and PAF was limited to the frontal/central electrode sites, while the correlations between psychometric intelligence and PAF at parietal/occipital electrode sites during the EO resting state did not reach statistical significance. However, they were in the same direction and did not differ significantly from the correlations between intelligence and PAF at frontal/central electrodes during EO. Based on these results, PAF measures from frontal/central electrodes might be better suited to investigate the relation between PAF and psychometric intelligence compared to parietal/occipital electrodes, but this difference seems to be rather marginal.

A clearer picture emerged from the differentiation between the EO and the EC resting states since psychometric intelligence was related to PAF during the EO but not during the EC resting states. The psychophysiological arousal level clearly increases, and alpha power decreases from closed to open eyes. This change has been interpreted as increased cortical activation in the EO compared to the EC resting state (Anderson & Perone, 2018; Barry et al., 2007; Barry & De Blasio, 2017; Başar et al., 1999). Therefore, it has been suggested that the EC condition represents a "true" resting state, whereas PAF in the EO condition reflects task-relevant preparatory processes or pre-task activation (Anderson & Perone, 2018, 2023; Angelakis, Lubar, & Stathopoulou, 2004; Angelakis, Lubar, Stathopoulou, & Kounios, 2004; Barry et al., 2007; Ben-Simon et al., 2008; Jann et al., 2010; Mahjoory et al., 2019). Proceeding from this assumption, our results indicate that the relation between PAF and psychometric intelligence necessitates at least a minimum of attentional activation during the measurement of PAF as in the EO condition. If this minimum of attentional activation is not reached in an EC condition, there is no association between PAF and psychometric intelligence. This conclusion is consistent with several previous reports, where PAF was unrelated to psychometric intelligence when measured during an EC condition (Finnigan & Robertson, 2011; Pahor & Jaušovec, 2016; Posthuma et al., 2001). Nevertheless, it remains unclear why previous studies on the relation between intelligence and PAF in EO resting states led to mixed results, with some studies reporting a positive association (Angelakis, Lubar, & Stathopoulou, 2004; Grandy et al., 2013; Leno et al., 2021) and other studies not finding this association (Ociepka et al., 2022). A main challenge for a clear interpretation is the fact that it is difficult to determine what participants exactly do during the resting state. If the PAF depends on the level of cognitive activity in the EO resting state, results might easily vary with the duration of the resting state and its position in the experimental course. When the resting state is positioned at the beginning of the session, it might be easier to relax compared to resting states embedded between several cognitive tasks, as in the present study, where evaluative processes regarding the last task or preparatory processes regarding the next task might take place. This idea would be in line with the results by Angelakis, Lubar, and Stathopoulou (2004), where the PAF after but not before a cognitive task was related to psychometric intelligence. Furthermore, disconnection from cognitive activation might become easier with a longer duration. Thus, in long resting states prior to cognitive tasks, the relation between PAF and intelligence might be weaker than in short resting states immediately following cognitive tasks. This highly tentative explanation, however, should be the subject of future studies. Regarding the relationship between temporal information processing and PAF, the index of dispersion in the TG task was positively associated with PAF measures at the parietal/occipital electrodes in the EO resting states prior to the TOJ and the DD task. Such an association was not found for the difference limen from the DD task and the 75%-TOJ difference threshold. Hence, a time-specific mechanism is unlikely to account for the relation between PAF and the index of dispersion. In contrast to the other two tasks, the TG task requires (long-term) memory processes in addition to time-specific processes when the standard stimulus is learned at the beginning and has to be remembered throughout the whole experimental session (McCormack et al., 1999; Rammsayer & Brandler, 2007). Maybe, these time-unspecific memory processes have caused the relation between the index of dispersion and PAF, which would be in line with the previously established link between PAF and memory performance (Clark et al., 2004; Grandy et al., 2013; Klimesch et al., 1990; Klimesch et al., 1993; Pahor & Jaušovec, 2016). This might also explain why neither Milton and Pleydell-Pearce (2017) with a duration discrimination task nor Venskus and Hughes

(2021) with a temporal estimation task could observe a functional relation between PAF and temporal information processing. Another study by Glicksohn et al. (2009) applied a time production task in which durations also had to be recalled from memory. PAF across all used electrodes was not related to the produced time in this study. However, a significant portion of the variance in produced time was explained when right- and left-hemisphere PAF were separated and then simultaneously submitted to a regression analysis, which indicated a mutual suppression effect of the left and right PAF on the produced time. This, however, could not be replicated in the present study due to high multicollinearity between right and left PAF variables when they were artificially separated.

Since only the index of dispersion was related to PAF but not the other timing measures, it was not surprising that there was also no association between PAF and TRP as a latent variable (see Figure 6). In other words, we found no evidence for the notion that PAF reflects a kind of master clock underlying the TRP latent variable (Rammsayer & Brandler, 2007; Surwillo, 1968). Due to this lack of a systematic association between PAF and TRP, it was not surprising that our mediation analysis failed to indicate a mediation of PAF on the TRP-intelligence relationship: If PAF is unrelated to TRP, it is unlikely that it can explain the relation between TRP and psychometric intelligence (but see Hayes, 2018).

In the following, some limitations of the present study have to be addressed, the first of which concerns the given time limit in the APM task. Previous studies have shown that a speeded intelligence test reflected more a measurement of working memory capacity than intelligence (Chuderski, 2013; Colom et al., 2015; Schubert et al., 2023). Thus, to rule out an effect of speededness on our results, we calculated the number of not-reached and incorrect items and related them to TRP. The results showed a significant negative association between the number of incorrect items and TRP but no relationship between the number of not-reached items and TRP, suggesting that the speededness of the intelligence test did not artificially influence its relation to TRP. The same was true for the correlations between APM and PAF variables. Thus, the time limit of the APM was probably generous enough to rule out a validity change. Another limitation arose from the PAF distribution in the present study, in which some subjects showed a PAF of 7 Hz, especially when measured with eyes open at frontal/central electrodes. This could indicate a drowsiness effect. However, when analyzing the changes in the frequency bands (theta, alpha, beta) between different time points (Jap et al., 2009), a possible drowsiness effect could not be found.

In sum, we were able to confirm the association between TRP and psychometric intelligence. In addition, we found psychometric intelligence to be related to PAF in frontal/central measures during the EO resting state. PAF, however, was unrelated to TRP, so that it could not explain the relation between psychometric intelligence and TRP as expected. The lacking relation between PAF and TRP does not necessarily mean that the rate of neural oscillations is not involved in TRP since we focused on alpha frequency and considered neither other frequency bands nor oscillations during cognitive activity in the present study. Other frequency bands, such as the gamma band, might be promising alternative candidates for the neural oscillations assumed to underlie psychometric intelligence and TRP. This might be plausible given the (to date relatively sparse) evidence for a functional relation between gamma activity and intelligence (Jaušovec & Jaušovec, 2005; Keizer et al., 2010; Stankov et al., 2006) and the involvement of gamma activity in temporal information processing (Kononowicz & Penney, 2016). An increasing number of studies also emphasize the role of cross-frequency couplings for the understanding of intelligence (for review, see Chuderski, 2016), as well as temporal information processing (for review, see van Wassenhove et al., 2019). Thus, the robust relationship between psychometric intelligence and TRP might not be explained by PAF but, nevertheless, provides a good basis for the investigation of the psychophysiological underpinning of psychometric intelligence.

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4.3 Article 3: Working memory updating as a mediator of the relation between temporal resolution power and psychometric intelligence

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Working Memory Updating as a Mediator of the Relation between Temporal Resolution Power and Psychometric Intelligence

Stefan J. Troche, Lisa M. Makowski, Olivier Pahud, & Thomas H. Rammsayer
Institute of Psychology, University of Bern, Bern, Switzerland

Address correspondence to:
Prof. Dr. Stefan J. Troche
University of Bern
Fabrikstr. 8
CH-3012 Bern
Switzerland
Email: stefan.troche@unibe.ch

Abstract

The temporal resolution power (TRP) hypothesis states that higher temporal acuity of the brain leads to better coordinated mental operations and, in turn, to better performance on tests of psychometric intelligence. Here, we examined this idea and concretized the vague construct "coordination of mental operations" through working memory (WM) updating. In 228 participants (age range: 18 to 30 years), TRP as derived from three timing tasks was significantly related to psychometric intelligence. Furthermore, WM updating was measured by Stankov's swaps task and depicted as a latent variable with increasing factor loadings to represent the increasing number of WM updates in different task conditions. WM updating correlated significantly with psychometric intelligence. In a latent mediation analysis, TRP and WM updating were still directly related to psychometric intelligence. Although the TRP-intelligence link did not substantially decrease in this model, the indirect path from TRP via WM updating to intelligence was statistically significant. This result suggests that higher TRP leads to temporally more precise mental representations in WM. Thereby, the present study provides a first answer to the question of how higher TRP translates into better performance and, eventually, to higher intelligence. Alternative views on the results are critically discussed.

Keywords: temporal resolution power; psychometric intelligence; working-memory updating

1. Introduction

The temporal resolution power (TRP) hypothesis holds that individual differences in psychometric intelligence are caused by individual differences in timing sensitivity and temporal acuity of the brain (Rammsayer & Brandler, 2007). Studies on the TRP hypothesis used different timing tasks, where small temporal differences between intervals, deviations from a regular rhythm, or the temporal order of events had to be perceived correctly (Rammsayer & Brandler, 2004). Consistently, a common TRP factor could be extracted from these heterogeneous timing tasks, which was associated with psychometric intelligence (Haldemann et al., 2012; Helmbold et al., 2007; Jastrzębski et al., 2021; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b).

As an explanation of this association, Rammsayer and Brandler (2007) put forward the idea that higher TRP leads to faster and better coordinated information processing. The assumption that better TRP leads to faster information processing was supported by studies which found that TRP and speed of information processing (SIP) were closely related and, moreover, that TRP mediated the relation between SIP and psychometric intelligence (Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007). The second assumption that higher TRP leads to better temporal coordination of mental operations was investigated by Troche and Rammsayer (2009). It was supposed that better coordination of mental operations should be especially obvious when information processing is subject to limited resources, as it is the case for working memory (WM) capacity. Using a latent variable approach, Troche and Rammsayer (2009) found the relationship between TRP and two aspects of psychometric intelligence (Processing Capacity and Processing Speed) to be completely mediated by WM capacity. This result supported the assumption that higher TRP leads to better temporal coordination of mental operations and, thus, to larger WM capacity, which in turn leads to better performance on intelligence tests. Most previously, Jastrzębski et al. (2021) replicated this result but interpreted it in another conceptual frame, which we will take up in the discussion section.

The interpretation of these results is complicated by the fact that WM capacity was very closely related to reasoning (or fluid intelligence) in both previous studies. Troche and Rammsayer (2009) reported regression coefficients of b=.92 for the WM capacity–Processing Capacity and b=.71 for the WM capacity–Processing Speed relationship. Similarly, in the two studies by Jastrzębski et al. (2021), the correlations between fluid intelligence and WM capacity were *r*=.85 and *r*=.88, respectively. With such a close relationship between two variables A and B, however, it is almost inevitable that the relationship between one of these two variables (e.g., A) and a third variable C (i.e., TRP), is more or less completely mediated by B. Such a mediating effect is hardly informative for the relation between A and C but just a reflection of almost virtually identical constructs A and B.

At least in part, this close relationship between WM capacity and intelligence might be due to the rather broad conceptualization of WM capacity as a latent variable derived from three (Troche & Rammsayer, 2009b) or even five WM tasks (Jastrzębski et al., 2021). Such a broad latent variable is highly representative of a multifaceted construct like WM capacity. At the same time, however, a specific interpretation of the latent variable "WM capacity" is hampered because limits of (short-term) memory might be as much the source of individual differences in WM capacity as the coordination of mental operations.

The goal of the present study was to examine how individual differences in TRP translate into individual differences in intelligence. Instead of a broad conceptualization of WM capacity, we focused on WM updating as a more specific process, which has been repeatedly shown to play a crucial role for understanding the WM-intelligence relationship (e.g., Friedman et al., 2006; Wilhelm et al., 2013). For this purpose, we employed Stankov's swaps task (Stankov & Crawford, 1993), where the number of required WM updates is systematically increased. More specifically, in this task, three letters are presented on a screen, and the participants' task is to swap, for example, the first and the third letter and to fill in the result. If the number of swaps is systematically increased, WM has to be updated not only once but twice or even three times, respectively. Using fixed-links modeling (Schweizer, 2008), we aimed to depict the *increasing* number of WM updates as a latent variable. With fixed-links modeling, individual differences, which change with the experimental manipulation, can be separated from more general individual differences in task performance, which do not vary between task conditions. For the present purpose, this allows for representing individual differences in WM updating and, concurrently, controlling for other individual differences unrelated to WM updating. The processing of the swaps task can be described in terms of Oberauer’s (2002) WM model with each swap requiring rapid updating of temporary bindings (Bateman, 2020). From the perspective of the TRP hypothesis, higher TRP should lead to temporally more precise bindings (and unbindings) in WM and, thus, to less errors in WM updating, which in turn should be related to higher intelligence. In other words, we assumed that WM updating would (partially) mediate the relationship between TRP and psychometric intelligence and, thereby, contribute to an explanation of how higher TRP translates into higher intelligence.

2. Method

Participants. Data of the same 118 women and 110 men as in the study by Pahud et al. (2018) were analyzed. The sample ranged from 18 to 30 years (M=22.0; SD=2.9) in age, and 104 participants were without academic education. Participants were paid 45 CHF; undergraduates in psychology could choose between money or course credits. The study protocol was approved by the local ethics committee of the Faculty of Human Sciences (University of Bern). Informed written consent was given by all participants before their participation.

Measurement of intelligence. As three major facets of intelligence, Processing Capacity, Processing Speed, and Memory were each assessed by six subtests from the Berlin Intelligence Structure test (Jäger et al., 1997). Each set of six subtests consisted of two numerical, two verbal, and two figural subtests. Performance scores on each subtest were *z* standardized and averaged for each facet. A *g* factor of psychometric intelligence was extracted from the three resulting scores by means of a confirmatory factor analysis (CFA). For more details see Pahud et al. (2018).

Duration discrimination (DD) task. This task consisted of two series of 32 trials to estimate the 25%- and the 75%-difference threshold, respectively. Each trial contained two empty auditory intervals separated by a 900-ms interstimulus interval. Onset and offset of an interval were marked by 3-ms clicks at an intensity of 70 dB via headphones. Duration of the standard interval was 50 ms. Duration of the comparison intervals varied according to Kaernbach's (1991) adaptive weighted-up-down procedure to estimate the duration of the comparison interval, which was perceived correctly as shorter (in the 25% series) or longer (in the 75% series) with a probability of 75%. Order of standard and comparison interval was pseudo-randomized. After each trial, participants indicated whether the first or the second interval was longer by pressing one of two designated keys followed by visual correctness feedback. The difference limen (DL; Luce & Galanter, 1963) was computed from the 25%- and the 75%- difference thresholds (determined from the last 20 trials of the two series). To yield positive correlations for a positive relationship between task performance and intelligence, the DL (and the 75%-TOJ threshold, see below) was inverted by multiplying it with -1.00.

Temporal-order judgment (TOJ) task. The TOJ task contained two series of 32 trials each. On each trial, a visual stimulus (presented via a red LED) and an auditory stimulus (white-noise burst presented via headphones with an intensity of 70dB) were presented. In one series, the onset of the tone preceded the onset of the light, while the onset of the light preceded the onset of the tone in the other series. The initial stimulus onset asynchrony (SOA) was 70ms in both series and varied in the following trials according to the adaptive weighted-up-down procedure (Kaernbach, 1991) to converge on a level of 75% correct responses. Stimuli were terminated 200 ms after the onset of the second stimulus. Trials of the two series were interleaved. Participants indicated whether the light or the tone was presented first by pressing one of two designated keys. The response was followed by visual correctness feedback. Across the last 20 trials of each series, the mean SOA was calculated and then averaged across the two series to represent the 75%-TOJ threshold.

Temporal generalization (TG) task. In the initial learning phase, participants were presented five times with a 75-ms standard tone (white-noise burst at an intensity of 70 dB), whose duration should be memorized. The experimental phase consisted of 64 trials, with a tone, which was the standard or a non-standard tone with a duration of 42, 53, 64, 86, 97, or 108 ms. After each tone, participants indicated whether the presented tone was the standard tone or not by pressing one of two designated keys. The response was followed by visual correctness feedback. The 64 trials were divided into eight blocks containing two standard tones and one of each non-standard tone, respectively. As dependent variable, the index of response dispersion (IRD; McCormack et al., 1999) was calculated.

Swaps task. The swaps task, adapted from Stankov and Crawford (1993), consisted of three conditions. Each condition contained 12 trials. The 36 trials were presented in pseudo-randomized order. In each trial, the letters J, K, and L were presented in pseudo-random order in the center of the computer monitor. At the top of the monitor, one, two, or three instruction lines were presented. The logic of each instruction line was "Swap x and y", with x, y Î {1,2,3} and x ¹ y (see Figure 1). In the 1-swap condition, only one instruction was given to swap two of the three letters. Participants typed in the resulting order of the three letters via a computer keyboard. In the 2-swaps condition, the interim result of the first swap had to be kept in mind so that the second instruction could be followed on this interim result. In the 3-swaps condition, a third swap had to be carried out on the second interim result. As dependent variables, the error rate per condition was determined and inverted to an accuracy measure (1 – error rate) so that higher values indicated better performance.

1-swap condition 2-swaps condition 3-swaps condition

Figure 1. Examples of trials from the three conditions of the swaps task.

Data analysis. All analyses were conducted with R-Studio (RStudio Team, 2021) using the following packages: lavaan (Rosseel, 2012), semTools (Jorgensen et al., 2022), psych (Revelle, 2022), corrplot (Wei & Simko, 2011), plyr (Wickham, 2011), and nortest (Gross & Ligges, 2015). Correlations between the dependent variables of the timing tasks, the accuracy in the swaps task, and the three aspects of intelligence were computed. From the three aspects of intelligence and the three timing tasks, a *g* factor of psychometric intelligence and a TRP factor were extracted by means of CFA. Accuracy measures from the swaps task were analyzed by means of fixed-links modeling (Schweizer, 2008) to extract more than one latent variable from the same set of manifest variables. For the swaps task, individual differences might not only exist in the coordination of WM updates but also in the encoding of sensory input, slips in response entering, fatigue, motivation, etc. These individual differences should not vary between the three task conditions so that they can be represented by a latent variable with the same factor loadings on all three manifest variables. On the other hand, individual differences in handling the increasing number of WM updates were depicted by a second latent variable with linearly increasing factor loadings {1;2;3} on the hit rates of the 1-, 2-, and 3-swaps conditions. The correlation between the two latent variables was set to zero for a clear separation.

In the final step, the measurement models of *g*, TRP, and the swaps task were combined in a latent mediation model to examine whether and to what extent WM updating mediates the relationship between TRP and psychometric intelligence. All relationships were tested one-tailed due to explicit expectations about their directions. The significance of indirect effects in this model was tested by means of the bootstrap sampling method (Hayes, 2018) with k=5000 bootstrap samples and a 90% confidence interval (CI). To correct for bias and skewness, the bias-corrected and accelerated bootstrap (BCa)-CI was computed (Hesterberg, 2011).

Model/data fit of SEMs was evaluated as good (or acceptable) as follows: a nonsignificant c^2-value, comparative fit index (CFI) $\geq .95$ ($\geq .90$), root mean square error of approximation (RMSEA) $\leq .05$ ($\leq .08$), and standardized root mean squared residual (SRMR) value $\leq .08$ ($\leq .10$) (Schweizer, 2010). Hancock’s H coefficient (Hancock & Mueller, 2001) was computed as construct reliability of latent variables.

3. Results

Since the BIS subtest scores were z standardized before being averaged, the means of the measures of “Processing Speed”, “Processing Capacity”, and “Memory” were close to 0, and their standard deviation close to 1. More details on the raw scores of the 18 subtests are provided by Pahud et al. (2018). Descriptive statistics of the dependent variables from the timing tasks and the swaps task are presented in Table 1.

Table 1. Descriptive statistics of measures from the timing tasks and the swaps task.

	Mean	SD	Min	Max	Skewness	Kurtosis
Duration Discrimination [DL in ms]	21	9	6	52	0.76	0.27
TG [IRD]	0.33	0.09	0.14	0.58	0.28	-0.30
TOJ [mean 75%-TOJ threshold in ms]	97	30	25	179	0.31	-0.41
1-swap condition [accuracy]	0.93	0.07	.57	1.00	-1.27	2.14
2-swaps condition [accuracy]	0.81	0.14	.21	1.00	-1.13	1.50
3-swaps condition [accuracy]	0.75	0.16	.14	1.00	-0.78	0.61

A full correlation matrix is presented in Table 2 in the supplementary material. Correlations between the three aspects of psychometric intelligence as well as correlations between performances on the three timing tasks were statistically significant. Thus, a *g* factor of psychometric intelligence and a factor representing TRP could be extracted. Their reliabilities were H=.79 and H=.39, respectively. When combined in an SEM, the regression from psychometric *g* on TRP was statistically significant, b=.604, *p*=.002, and the model showed a good fit, $\chi^2(8)=3.034$, *p*=.932, CFI=1.000, RMSEA=.000, SRMR=.015.

Correlations between accuracy measures from the three swaps task conditions were also statistically significant ranging from *r*=.18 to *r*=.45. Computing the fixed-links measurement model explained in the method section revealed that the variance parameter of the latent variable with constant factor loadings was not significant (and even negative) indicating that individuals differed primarily in the processes, which were experimentally manipulated among the task conditions. Therefore, we omitted the latent variable with constant factor loadings in a next step, which led to an acceptable data description, $\chi^2(2)=4.706$, $p=.095$, CFI=.936, RMSEA=.077, SRMR=.021. The variance parameter of the latent variable was statistically significant, $j_{\text{increasing}}=0.143$, $z=6.548$, $p<.001$, and Hancock's reliability coefficient was H=.63.

We also tested whether this fixed-links model described the data better than a model with factor loadings restricted to be equal {1;1;1}. The latter model led to a poor data description, $\chi^2(2)=23.316$, $p<.001$, CFI=.499, RMSEA=.216, SRMR=.127. Furthermore, a congeneric model could not be meaningfully compared to the fixed-links model with increasing factor loadings. However, in the congeneric model the factor loadings also increased monotonically from the 1- to the 3-swaps condition {1;3.86;5.73}. Thus, it seems appropriate to proceed with the fixed-links measurement model, where one latent variable was extracted with linearly increasing factor loadings referring to the increasing number of WM updates.

When combined with the measurement model of psychometric intelligence, the regression coefficient of the WM updating variable on psychometric *g* was statistically significant, b=.601, $p<.001$. The model showed a good fit, $\chi^2(10)=14.259$, $p=.162$, CFI=.985, RMSEA=.043, SRMR=.057.

In a final step, we combined all three measurement models to examine whether WM updating would mediate the TRP-intelligence relationship. The resulting mediation model described the data well, $\chi^2(26)=27.595$, $p=.379$, CFI=.995, RMSEA=.016, SRMR=.052. All three regression coefficients were statistically significant as can be taken from Figure 2. The same was true for the indirect effect from TRP via WM updating to *g*, $b_{\text{TRP-WMup-}g}=.195$, $p<.01$

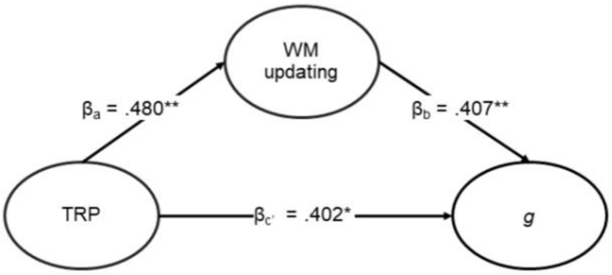

Figure 2. Mediation model testing the link between TRP and *g* via the latent variable WM updating from the swaps task (standardized coefficients).
p*<.05,*p*<.01

To further evaluate the statistical significance of the direct and indirect effects, bootstrapped (Bca) 90%-CIs were computed. The unstandardized regression coefficients and their confidence intervals were $b_{\text{TRP-WMupdating}}$=.424 [.203,.829], $b_{\text{WMupdating-}g}$=.515 [.172,.803], and $b_{\text{TRP-}g}$ =.449 [.125,1.069]. The unstandardized indirect effect was .218 with a confidence interval ranging from .108 to .498. Thus, the CI did not include zero corroborating the statistical significance of the indirect effect and the conclusion that the TRP-*g* relationship was partially mediated by WM updating.

4. Discussion

The present study examined the assumption that the relationship between TRP and psychometric intelligence was mediated by WM updating. In contrast to Stankov and Schweizer (2000), we could not extract a latent variable representing general individual differences in the swaps task (regardless of the number of WM updates). However, the extracted latent variable reflected the increasing individual differences with the increasing number of WM updates by increasing factor loadings from the 1- to the 3-swaps condition. This latent variable was related to both TRP and psychometric intelligence. The decrease of the direct path from TRP to intelligence (from .604 to .402), when WM updating was added as potential mediator, was not statistically significant. However, the indirect path from TRP via WM updating on intelligence was significant indicating that WM updating partially mediated the relationship between TRP and psychometric intelligence. With this finding, the question of how higher TRP translates into higher intelligence can be tentatively answered as follows: Higher TRP leads to less error-prone WM updating, which might be explained by temporally more precise bindings (and unbindings) of the three letters to their (changing) positions. Making fewer updating errors, in turn, facilitates better performance in intelligence tests, when for example different possible solutions for a given test item are tried, discarded, or chosen.

It should be noted that the present interpretation of the results is guided by the framework of the TRP hypothesis. Certainly, alternative views on the present results are conceivable. One stems from research on the relationship between more general sensory discrimination ability and psychometric intelligence, which was previously found to be completely explained by WM capacity (Jastrzębski et al., 2021; Troche et al., 2014; Tsukahara et al., 2020). Therefore, it has been argued that sensory acuity per se is unrelated to intelligence. Rather, sensory discrimination tasks would require WM-related processes when a first stimulus is temporarily stored and compared with a second stimulus regarding, for example, their pitch or duration. Hence, the sensory aspects of sensory discrimination (related specifically to the auditory or visual system) might be less important for the relation to intelligence than more central aspects such as the accuracy of the stimuli's mental representations in an amodal WM. Consequently, Jastrzębski et al. (2021), who found WM capacity to explain the complete relationship between intelligence and temporal as well as non-temporal sensory discrimination, concluded that WM capacity is the basic mechanism shared by TRP and psychometric *g* so that TRP plays "no explanatory role for intelligence" (p. 1289). The main difference between this interpretation and the interpretation based on the TRP hypothesis is the assumed causal direction of the effects. The TRP hypothesis assumes that higher TRP leads to higher WM capacity and, in turn, to higher psychometric intelligence (Troche & Rammsayer, 2009b). Jastrzębski et al.'s (2021) WM capacity approach, on the contrary, states that higher WM capacity leads to better performance on TRP tasks and, concurrently, to higher psychometric intelligence. With latent regression models, it is difficult, if not impossible, to decide on the causal direction of the effects. In the present study, changing the direction of the regression from TRP to the latent variable with increasing factor loadings from the swaps task would only marginally change the regression coefficients and the model/data fit (but see Jastrzębski et al., 2021, for another result on their data).

Most importantly, in previous studies, WM capacity and psychometric intelligence were so closely related to each other that they were almost interchangeable (Jastrzębski et al., 2021; Troche & Rammsayer, 2009b; Troche et al., 2014; Tsukahara et al., 2020). Consequently, it was hardly possible for a third variable, such as TRP, to explain unique portions of variance in psychometric intelligence independently from WM capacity. This also complicates deductions about specific processes and their interplay to explain individual differences in psychometric intelligence. From this point of view, the focus on a more specific process such as WM updating, which has been discussed to be highly critical for WM capacity limitations (Oberauer, 2018), is better suited to investigate the mechanisms underlying the relationship between TRP and psychometric intelligence. This is, the more specific latent variable with increasing factor loadings extracted from the three conditions of the swaps task can be interpreted according to its reference to the differences between the task conditions, i.e., the number of WM updates. The more WM updates are required, the closer the relation to TRP. The processing of short durations, as used in the timing tasks of the present study, has been shown to be sensory-perceptual in nature and not cognitively mediated (Ivry & Spencer, 2004; Lewis & Miall, 2003; Rammsayer & Lima, 1991). This challenges the assumption that the relationship between TRP and *g* can be explained in terms of common WM demands. Rather, the results of our mediation analysis suggest that better temporal acuity facilitates WM updating as an aspect of general information processing. This conclusion is consistent with the general notion that higher TRP leads to better information processing (cf., Burle & Bonnet, 1997, 1999; Rammsayer & Brandler, 2007; Surwillo, 1968). But again, considering the correlational nature of the present analyses, this interpretation should be viewed with caution.

Finally, it should be noted that most of the TRP–*g* link was not mediated by WM updating. As mentioned in the introduction, a second path from TRP to *g* can be seen in SIP. Whether the two paths from TRP to *g* (via SIP and via WM updating) are independent or (as we believe) overlap, will be an important next step in future studies. Furthermore, with only one task assessing WM updating, the operationalization might have been rather narrow. We have described the advantages of this procedure above. However, future research should use more than only one task to extract latent variables representing WM updating and to combine them to a higher-order latent variable. This would elucidate whether the present results can be generalized to other WM updating tasks and whether a broader operationalization of WM updating will show a more pronounced mediation effect on the relationship between TRP and psychometric intelligence. Further investigations are necessary to exclude possible confounding variables, to pinpoint the specific aspects of WM updating (Kessler & Meiran, 2008) involved in the mediation, and to determine convergent validity of the latent variable representing WM updating. However, the present study succeeded in showing a plausible way of how individual differences in TRP translate into individual differences in intelligence by facilitating WM updating.

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4.4 Additional Analysis: Examining the links between duration discrimination performance, gamma and theta coherence with regard to differences in psychometric intelligence

4.4.1 Introduction

According to the TRP hypothesis, it has been repeatedly shown that individuals who are more accurate in their temporal accuracy and sensitivity also process information faster (Helmbold et al., 2007; Pahud et al., 2018), coordinate their mental operations better (Troche & Rammsayer, 2009b) and, in turn, also have higher psychometric intelligence scores (Rammsayer & Brandler, 2007). These differences in TRP might be explained by an internal timing mechanism referred to as an internal master clock, which was proposed to be reflected in the rate of neural oscillations (Rammsayer & Brandler, 2002, 2007; Surwillo, 1968). As a consequence, it can be assumed that the faster the oscillation rate, the higher the temporal resolution of this master clock. This indicates that based on the TRP hypothesis and the assumption of this internal master clock, the relationship between psychometric intelligence and TRP would be due to sensory processing differences.

In contrast to this view, other studies argued that the relationship between psychometric intelligence and a bottom-up process such as TRP, or sensory discrimination ability cannot be attributed to differences in sensory acuity alone. More specifically, they could provide evidence that the association of TRP, or sensory discrimination ability with psychometric intelligence could be completely explained by WMC differences (Jastrzębski et al., 2021; Troche et al., 2014; Tsukahara et al., 2020). This indicates that individuals with higher TRP, or more accurate sensory discrimination ability, showed higher psychometric intelligence because a higher WMC is also needed during sensory task processing. This can be seen in a sensory discrimination task, such as an auditory duration discrimination task (DD), in which participants must first encode the duration of a presented stimulus (e.g., a standard tone of 1000 ms), then actively retain the information in their head while encoding a second stimulus (e.g., a comparison tone of 750 ms) and then compare the durations of the two stimuli. As these processes rely heavily on working memory, an individual with higher capacity will be able to store, retain, and process the different tone lengths more accurately, which in turn will lead to more precise discriminations (Jastrzębski et al., 2021; Mashburn et al., 2020; Tsukahara et al., 2020). However, the quality with which these processes can occur should also depend largely on how much attention is focused on the task-relevant information while task-irrelevant information is tuned out (Tsukahara et al., 2020). It was therefore argued that these processes should rely on attention control, a top-down process required to organize and modulate information processing in order to behave in a goal-oriented manner (Burgoyne et al., 2023; Kane & Engle, 2003; Mashburn et al., 2020). This process has been shown to be closely linked to WMC (Shipstead et al., 2014; Unsworth et al., 2021; Unsworth & Spillers, 2010) and psychometric intelligence while even explaining the relationship between WMC and psychometric intelligence (Burgoyne et al., 2020; Heitz et al., 2005; Kovacs & Conway, 2016; Mashburn et al., 2020). In this context, it has been argued that attention control in working memory is important for retaining relevant information and suppressing irrelevant information. As this facilitates information processing, it may, in turn, explain why individuals with higher attention control also exhibit a higher level of psychometric intelligence. Based on this, a more recent study investigated the extent to which attention control can explain the relationship between sensory discrimination ability and psychometric intelligence. It could show that it fully explains their relationship (Tsukahara et al., 2020). From this perspective, it might also be interesting to see to what extent attention control can explain the relationship between TRP and psychometric intelligence. However, no study has investigated this to date. It is also not known how TRP is related to attention control. What is known, however, is based on single temporal information processing tasks such as duration discrimination tasks or temporal generalization tasks that are also used when deriving TRP (Rammsayer & Brandler, 2004, 2007). In terms of these tasks, it was shown that how much attention was directed to the task had an impact on temporal accuracy (Bausenhart et al., 2016; Broadway & Engle, 2011; Ciria et al., 2019; Dyjas et al., 2012; Ogden, 2014; van Rijn, 2016). These findings were interpreted in terms of the further developments of the pacemaker-accumulator models, for example, the Attentional Gate Model (Block & Zakay, 1997; Zakay & Block, 1996). Based on this model, if more attention is directed during the encoding phase, more pulses or ticks from the internal clock or pacemaker can be processed in a so-called accumulator, which enables more precise and, therefore, more accurate processing of the stimulus duration (Block & Zakay, 1997; Grondin, 2010; van Wassenhove et al., 2019; Zakay & Block, 1996). However, the extent to which this attention control is also important in explaining why individuals based on the rate of an internal master clock differ in TRP and thus show higher psychometric intelligence remains to be seen.

For the investigation of possible individual differences in ongoing cognitive processes during a task, e.g., a temporal discrimination task, the analysis of frequency bands as recorded in the EEG can be used (Başar et al., 1999; Cohen, 2014). As mentioned before, differences in TRP are explained by an internal master clock that should be reflected in the rate of neural oscillations. Based on this, we investigated in Study 2 (Makowski & Troche, 2023) to which this master clock can be reflected by a frequency measure called peak alpha frequency (PAF). It could be shown that participants showed pronounced differences (Grandy et al., 2013; Hilger et al., 2022). Contrary to expectations, however, no significant association was found between TRP and PAF. A possible explanation might lie that, as argued previously, most cognitive processes are not only associated with a specific area of the brain but involve the activation of different areas (Bowyer, 2016; Decker et al., 2017). In this turn, a recent meta-analysis based on fMRI findings could provide evidence that during temporal information processing also several regions were activated (Nani et al., 2019) concerning the detection of the internal clock as the sensory process of time processing. Also, regarding psychometric intelligence, it has been shown that individuals differ not only in the activation of one area within a frequency band but also in the patterns of activation over different electrodes (Hilger et al., 2022). Thus, focusing only on the power or frequency at specific electrodes within one frequency band might be too limited. Although we implemented all 64 electrodes in Study 2, we did not focus on how the activity between these electrodes was related. In order to show the relations or synchronizations between electrodes, a coherence analysis can be conducted (Fries, 2005, 2015). This analysis can be quantified with the magnitude-squared coherence in which the phase information is weighted by the magnitude information within a specific frequency band (Malekpour et al., 2018). This results in a coherence value between 0 and 1 for each electrode pair, with 1 indicating a high similarity in the measured signal in two electrodes and 0 indicating no similarity.

Previous studies could show that individual differences in sensory processing can be studied on the psychophysiological level by means of gamma coherence (Karakaş et al., 2001; Strüber & Herrmann, 2022; von Stein & Sarntheim, 2000). Due to the different electrodes used and the given sensory tasks, it cannot be concluded to what extent there were modality-specific or modality-independent activations of sensory areas. Furthermore, it should be noted that other studies assume that gamma coherence activity can also be interpreted as a top-down mechanism, which is again taken up in the discussion (Bonnefond & Jensen, 2015; Leicht et al., 2021). Differences in terms of gamma coherence were also investigated in terms of psychometric intelligence. It could be shown that gamma coherence (25-60 Hz) during resting state with eyes closed over the whole scalp (Lee et al., 2012) and gamma coherence (31-49 Hz) between occipital and parietal electrodes when measured during a cognitive task were positively related to psychometric intelligence (Jaušovec & Jaušovec, 2005). However, as these two studies also differ in their measurements and the electrode pairs found, no general statements can be made. Nevertheless, these findings corroborate previous behavioral studies

(Acton & Schroeder, 2001; Deary, 1994; Helmbold et al., 2006; Jastrzębski et al., 2021; Troche et al., 2014; Troche & Rammsayer, 2009a; Tsukahara et al., 2020) by showing that individuals with higher psychometric intelligence also exhibit a more pronounced sensory process, as indicated by a higher gamma coherence. In terms of temporal information processing, only one study investigated ongoing gamma coherence during temporal information processing but did investigate not performance-related differences (Hoodgar et al., 2022). This study showed during the encoding of a shorter stimulus (500 ms) gamma coherence between left-sided temporal and central and right-sided frontal and temporoparietal electrode sites. Gamma coherence was also present during the encoding of a longer stimulus (1000 ms) but between frontal and central, right frontal and left temporal, left-sided frontal, and between left-sided frontal and parietal electrode sites. To the best of our knowledge, no study to date has investigated the performance-related differences in gamma coherence that can be related to temporal information processing performance.

In contrast to the notion of an internal master clock that might explain the relationship between TRP and psychometric intelligence, it might also be the case that the relationship between TRP and psychometric is due to common attention control processes (Tsukahara et al., 2020). In order to investigate individual differences in attention control on the psychophysiological level, previous studies have focused on the theta coherence measured between frontal and parietal electrodes (Basharpoor et al., 2021; Eschmann et al., 2020; Karakaş, 2020; Myers et al., 2021; Nurislamova et al., 2019; Sauseng et al., 2005, 2006, 2007; von Stein & Sarntheim, 2000). Within these studies, it was shown that theta coherence increased when more attention control was needed. In line with this and previous behavioral findings, it could also be shown that psychometric intelligence was positively associated with frontal-parietal theta coherence measured during resting state (Anokhin et al., 1999; Granados-Ramos et al., 2019; Jaušovec & Jaušovec, 2000; Lee et al., 2012; Razoumnikova, 2003; Thatcher et al., 2005) as well as during task processing (Anokhin et al., 1999; Okuhata et al., 2009; Pahor & Jaušovec, 2016; Weiss et al., 2000). These findings align with previous behavioral findings by showing that individuals with higher psychometric intelligence exhibit more attention control, which might facilitate their information processing (Burgoyne et al., 2023; Engle et al., 1999; Heitz et al., 2005; Mashburn et al., 2020). Regarding temporal information processing, only one study to date investigated the theta coherence during temporal information processing (Hoodgar et al., 2022). However, as for gamma coherence, this study was also limited to a task approach. They observed theta coherence between frontal and temporal electrodes during the encoding of the shorter interval (500 ms), and between frontal and temporal, central and temporal, central and occipital, and between temporal and occipital electrodes during the encoding of a longer duration (1000 ms). Thus, in terms of temporal information processing, little is known about how the theta and gamma coherence might be related to performance differences. Only some studies that are based on power differences in the theta frequency band indicate that an increased theta power is associated with higher performance in temporal information processing, as in line with previous behavioral findings (Gu et al., 2015; Hsieh et al., 2011; Martins e Silva et al., 2022; Roberts et al., 2013; but also see Kononowicz & Rijn, 2015).

Considering these previous findings, this study aimed to provide initial indications of the extent to which individual differences in temporal accuracy can be attributed to differences in sensory processing or/and attention control involved during the encoding of a temporal information processing task. It was further aimed to examine how these associations differ between individuals with higher and lower intelligence. This extreme group analysis was based on previous studies providing compelling evidence on the behavioral and psychophysiological levels in terms of differences in sensory processing (Jastrzębski et al., 2021; Troche et al., 2014; Troche & Rammsayer, 2009a; Tsukahara et al., 2020) and attention control (Burgoyne et al., 2023; Engle et al., 1999; Heitz et al., 2005; Mashburn et al., 2020). In addition, the present study's analysis was based on the TRP hypothesis, and the results were intended as a first step toward examining the relationship between TRP and psychometric intelligence in more detail. Therefore, the analyses of the present studies focused on one of the TRP tasks, namely the temporal discrimination task with a standard interval of 1000 ms. With this in mind, four different hypotheses were investigated, with two of them focusing on differences in sensory processing, as measured with the temporal-parietal gamma coherence, and two other focusing on differences in attention control, as measured with frontal-parietal theta coherence. To this end, a positive relationship was expected between temporal accuracy and sensory processing (temporal-parietal gamma coherence) as well as between temporal accuracy and attention control (frontal-parietal theta coherence). Based on the second aim in terms of group differences, an interaction effect was expected for both relationships with psychometric intelligence. In this turn, it was expected that these relationships would be more pronounced in individuals with higher psychometric intelligence.

4.4.2 Methods

4.4.2.1 Sample. The sample consisted of 100 healthy and right-handed participants (M_{age} = 22.8, SD_{age} = 2.9). The number of participants was selected from the sample of Study 2 (Makowski & Troche, 2023), and 27 additionally recruited participants. From this sample of

N = 156, 100 subjects were selected based on their sum score in the Raven's Advanced Matrices Test (APM). For this purpose, a median split of the APM score was conducted for the sample of *N* = 156. It resulted in two groups, one with higher and one with lower intelligence scores. From these groups, the 50 participants with the highest intelligence scores and 50 participants with the lowest intelligence scores were selected, ultimately leading to the final sample of *N* = 100. The groups differed significantly in their APM score (see Table 2). In Table 1, the sample size, average age, standard deviation of age, minimum and maximum age, and distribution by gender and educational level are displayed. Both groups were balanced in terms of gender and age distribution. Only minimal differences were found concerning the highest level of education.

Table 1

Description of the sample in terms of age, gender, and highest level of education attained

Group	*N*	M_{age}	SD_{age}	Min_{age}	Max_{age}	Gender		Highest education level	
						m (*N*)	w (*N*)	VS (*N*)	HET (*N*)
low APM	50	22.7	2.7	18	29	15	35	7	43
high APM	50	22.9	3.1	19	31	15	35	1	49

Note. M = mean, *SD* = standard deviation, Min = minimal value, Max = maximal value, m = men, w = women. VS = vocational school as highest educational training, HET = higher educational training. Higher educational training implies all academic training, including and higher than higher high school (*Matura*) in Switzerland.

4.4.2.2 Procedure. The procedure details are equivalent to the ones described in Makowski and Troche (2023). However, the present study only focused on the short form of the advanced matrices test (APM), the DD task, and the EEG measurement during the DD task measurement.

4.4.2.3 Psychometric intelligence test. To measure psychometric intelligence, a short version of the Raven's advanced matrices test (APM) with 18 items was used (Sefcek et al., 2016). Detailed information can be found in Makowski and Troche (2023). For the statistical analysis, the sum score was calculated.

4.4.2.4 Duration discrimination task. Temporal information processing was assessed with an auditory duration discrimination task using a tone (1000 Hz) with a standard duration of 1000 ms. In each trial, participants were presented with a standard (1000 ms) and a comparison stimulus (varying duration). In total, there were 64 trials. In 32 of them, the comparison interval was longer than the standard interval, and in the other 32, it was shorter. The order of standard and comparison intervals was randomized and separated by an inter-stimulus interval of 900 ms. After the presentation of both intervals, participants had to decide which interval had been longer by pressing a designated key. They received no feedback, and the subsequent trial started after a 1500 ms inter-trial interval.

The comparison stimulus duration was varied according to the adaptive weighted-up-down procedure (Kaernbach, 1991). Details on this procedure can be found in the Article of Study 2 (Makowski & Troche, 2023). This procedure resulted in two thresholds: a 25%-difference threshold for the series in which the comparison stimulus was shorter and a 75%-difference threshold for the other series in which the comparison stimulus was longer than the standard stimulus. Only the last twenty trials were used to compute these thresholds. As a performance measure of the DD task performance, the difference limen (DDL) was then calculated by dividing half of the interquartile range [(x.75-x.25)/2]. Smaller values indicated better performance (Luce & Galanter, 1963). For further analyses, the DDL values were inverted so that higher values indicated a better performance. For the regression analyses, they were also z-standardized.

4.4.2.5 EEG preprocessing and coherence analysis. The EEG was recorded with a 64-channel Biosemi ActiveTwo EEG system (Biosemi, 2022) with active gel electrodes and a sampling rate of 2048 Hz. Detailed information on the electrode montage and preprocessing can be found in Makowski and Troche (2023). The preprocessing and subsequent coherence analysis were conducted in Brain Vision Analyzer (Version 2.2.1.8266; Brain Products, 2019). After the preprocessing, the data was first segmented for the prestimulus phase before the standard interval (-900 to 0 ms around the start of the standard interval) as well as the stimulus phase of the standard interval (0 to 1000ms around the beginning of the standard interval) for each individual. Then, another semiautomatic raw data inspection was conducted on these prestimulus and stimulus intervals with the following settings: maximal allowed voltage step of 50 µV/ms, the minimal allowed amplitude of -100 µV, and the maximally allowed amplitude of 100 µV. The artifacts marked by this algorithm were then all checked manually. Then, an FFT was conducted with a 1 Hz frequency resolution to extract the complex spectral values. This was followed by a coherence analysis to derive magnitude-squared coherence between frontal and parietal and between temporal and parietal electrodes. In order to minimize possible volume conduction effects, the investigation concentrated on electrodes at least 5 cm apart (Keil et al., 2022; Nunez et al., 1997). It was thus focused on the following 48 coherence pairs for theta coherence: F1-P3, F1-P4, F1-P5, F1-P6, F1-P7, F1-P8, F2-P3, F2-P4, F2-P5, F2-P6, F2-P7, F2-P8, F3-P3, F3-P4, F3-P5, F3-P6, F3-P7, F3-P8, F4-P3, F4-P4, F4-P5, F4-P6, F4-P7, F4-P8, F5-P3, F5-P4, F5-P5, F5-P6, F5-P7, F5-P8, F6-P3, F6-P4, F6-P5, F6-P6, F6-P7, F6-P8, F7-P3, F7-P4, F7-P5, F7-P6, F7-P7, F7-P8, F8-P3, F8-P4, F8-P5, F8-P6, F8-P7, F8-P8. The following 32 coherence pairs were focused on for gamma coherence, derived from the prestimulus and stimulus phase separately: FT7-P3, FT7-P4, FT7-P5, FT7-P6, FT7-P7, FT7-P8, T7-P3, T7-P4, T7-P5, T7-P6, T7-P7, T7-P8, TP7-P3, TP7-P4, TP7-P6, TP7-P8, FT8-P3, FT8-P4, FT8-P5, FT8-P6, FT8-P7, FT8-P8, T8-P3, T8-P4, T8-P5, T8-P6, T8-P7, T8-P8, TP8-P3, TP8-P4, TP8-P5, TP7-P7. The coherence between TP7 and P5, TP7 and P7, TP8, and P6, as well as TP8 and P8 were omitted because they were too close to each other. These resulting coherence values between frontal and parietal electrodes were then exported for the theta frequency band (4-7 Hz) and between temporal and parietal electrodes for the gamma frequency band (30-49 Hz).

4.4.2.6 Statistical analyses. Statistical analyses were conducted with R (4.3.1, R Core Team, 2023) and R-Studio version (2023.06.1, RStudio Team, 2022). The following packages were used to create the data set and descriptive statistics: readxl (1.4.2, Wickham et al., 2023), tidyverse (2.0.0, Wickham, 2023), dplyr (1.1.2; Wickham et al., 2023), e1071 (1.7-13; Meyer et al., 2023), writexl (1.4.2; Ooms & McNamara, 2023). For the correlational and inferential statistics, the psych (2.3.6; Revelle, 2023), the rstatix (0.7.2; Kassambra, 2023), the flextable (0.9.2; Gohel & Skintzos, 2023), the Hmisc (5.1-0; Harrell Jr, 2023) as well as the cocor (1.1-4; Diedenhofen, 2023) packages were used.

First, the descriptive statistics were calculated for all theta coherence values between frontal and posterior electrodes, separately for prestimulus and stimulus phases. These coherence values were then Fischer z-transformed and compared between the prestimulus and the stimulus phases to determine for which coherence pairs (e.g., F3-P3) there was a significant increase or decrease from the prestimulus to the stimulus phase. For this purpose, paired t-tests were performed, which were corrected for multiple comparisons with Bonferroni-Holm. This procedure was repeated for the gamma coherence values between temporal and parietal electrodes. For theta and gamma coherence values, there were no significant differences between the prestimulus and stimulus phase for each pair (e.g., F3-P3). Therefore, the following analyses focused only on the stimulus phase.

The coherence values were then averaged per frequency band to minimize the number of variables (for similar procedures, see Reiser et al., 2012; Rominger et al., 2022). Since previous studies indicated a possible hemisphere effect in terms of temporal information processing (Hoodgar et al., 2022), it was differentiated into the intrahemispheric left, intrahemispheric right, and interhemispheric coherence values. This resulted in the following four mean coherence values for theta measured during the standard duration interval: right frontal-posterior (F2-P4, F2-P6, F2-P8, F4-P4, F4-P6, F4-P8, F6-P4, F6-P6, F6-P8, F8-P4, F8-P6, F8-P8), left frontal-posterior (F1-P3, F1-P5, F1-P7, F3-P3, F3-P5, F3-P7, F5-P3, F5-P5, F5-P7, F7-P3, F7-P5, F7-P7), left frontal to right posterior (F1-P4, F1-P6, F1-P8, F3-P4, F3-P6, F3-P8, F5-P4, F5-P6, F5-P8, F7-P4, F7-P6, F7-P8) and right frontal to left posterior theta coherence (F2-P3, F2-P5, F2-P7, F4-P3, F4-P5, F4-P7, F6-P3, F6-P5, F6-P7, F8-P3, F8-P8, F8-P7). For gamma coherence, this also resulted in the following four coherence variables: right temporal-parietal (FT8-P4, FT8-P6, FT8-P8, T8-P4, T8-P6, T8-P8, TP8-P4), left temporal-parietal (FT7-P3, FT7-P5, FT7-P7, T7-P3, T7-P7, T7-P7, TP7-P3), left temporal to right parietal (FT7-P4, FT7-P6, FT7-P8, T7-P4, T7-P6, T7-P8, TP87-P4, TP7-P6, TP7-P8) and right temporal to left parietal gamma coherence (FT8-P3, FT8-P5, FT8-P7, T8-P3, T8-P5, T8-P7, TP8-P3, TP8-P5, TP8-P7). The descriptive statistics for these eight coherence variables, DDL, and APM performance were then calculated per group and tested for group differences with independent t-tests. Then, the Pearson correlations between all coherence variables and DDL were calculated per group. These results were then corroborated using multiple regression analyses in which the DDL was implemented as the dependent variable and the group variable based on APM performance as well as the eight coherence variables as independent variables. Prior to these analyses, their requirements were checked which showed that they were met.

4.4.3 Results

Table 2 presents the descriptive statistics of the APM sum score, DDL, and mean Fischer z-transformed gamma and theta coherence measured during the stimulus phase. As these values were Fischer z-transformed before being averaged, the range of values can no longer vary from 0 to 1 (Bortz & Schuster, 2010). Based on the skewness and kurtosis shown, all values showed to be normally distributed. All values were additionally tested for group differences with independent t-tests. There were no group differences in DDL or coherence variables. The groups only differed significantly in their APM sum score.

Table 2

Descriptive statistics and t-tests of psychometric intelligence performance (APM), duration discrimination performance (DDL), and mean gamma and theta coherence values

Variable	Higher intelligence scores						Lower intelligence scores							
	M	*SD*	Min	Max	S	K	*M*	*SD*	Min	Max	S	K	*t*	*d*
APM	15	1	14	18	0.37	-0.89	10	2	6	12	-0.58	-0.81	-16.9***	-3.39
DDL	139	47	62	269	0.76	0.08	144	55	58	278	0.61	-0.52	.52	0.10
Gamma temporal-parietal (l)	0.26	0.16	0.06	0.86	1.12	1.79	0.25	0.17	0.03	0.77	0.99	0.86	-0.18	-0.04
Gamma temporal-parietal (r)	0.29	0.14	0.07	0.75	1.11	1.43	0.32	0.20	0.06	0.95	0.98	0.63	0.99	0.20
Gamma left temporal and right parietal	0.15	0.11	0.02	0.60	1.73	3.43	0.16	0.11	0.03	0.49	1.13	0.85	0.20	0.04
Gamma right temporal and left parietal	0.17	0.11	0.03	0.55	1.35	1.83	0.18	0.12	0.03	0.47	0.93	0.11	0.55	0.11
Theta frontal-parietal (l)	0.21	0.08	0.07	0.46	0.97	0.98	0.18	0.07	0.06	0.39	0.35	-0.08	-1.54	-0.31
Theta frontal-parietal (r)	0.22	0.09	0.07	0.46	0.80	0.23	0.22	0.09	0.08	0.42	0.45	-0.80	0.04	0.01
Theta left frontal and right parietal	0.15	0.08	0.03	0.40	1.54	2.00	0.13	0.06	0.04	0.35	1.35	1.79	-1.14	-0.23
Theta right frontal and left parietal	0.15	0.08	0.04	0.40	1.28	1.19	0.16	0.09	0.03	0.39	0.95	-0.17	0.25	0.05

Note. Per group *N* = 50. *M* = mean, *SD* = standard deviation, Min = minimum, Max = maximum, S = skewness, K = kurtosis. (r) = right, (l) = left, DDL = difference limen (performance measure of the duration discrimination task). Displayed are the mean Fischer z-transformed gamma coherence values measured between temporal and parietal electrodes as well as the mean Fischer z-transformed theta coherence values measured between frontal and parietal electrodes.

In Table 3, the results of the Pearson correlations between inverted DDL, mean gamma, and theta coherence variables per group are displayed. Concerning the DDL, there was a small negative and significant correlation with theta coherence measured between the left frontal and right parietal electrodes only in the group with lower intelligence scores. This correlation remained insignificant in the group with higher psychometric intelligence.

However, the correlation did not differ significantly from the one found in the group with lower intelligence ($z = -1.11$, $p = .277$). No other significant correlations existed between DDL and gamma or theta coherence in any of the groups. When the correlation between DDL and theta coherence (left frontal, right parietal) was calculated overall participants, also a significant small and negative correlation could be found ($r = -.22$, $p = .028$).

Regarding the coherence values within the same frequency band, highly significant and positive associations could be shown in both groups. Additional paired and Bonferroni-Holm corrected t-tests showed that although these coherence scores were positively related, they were still significantly different ($p < .05$).

As for the associations between gamma and theta coherence, there were two significant associations in the higher psychometric intelligence group, namely between right frontal-parietal theta coherence and interhemispheric gamma coherence of the left temporal and right parietal electrodes and between interhemispheric theta coherence of the right frontal and left parietal electrodes and right temporal-parietal gamma coherence. Five significant and positive associations were found in the group with lower psychometric intelligence scores. Three were between interhemispheric theta coherence (left frontal, right parietal) and all gamma coherence variables except the one measured on the right side. The other two significant associations were found between right-sided theta coherence and right-sided gamma coherence and interhemispherical measured gamma coherence (right temporal, left parietal). Although the correlation patterns showed differences between the groups, the significant associations found in the group with lower psychometric intelligence scores did not differ significantly from those found in the group with the higher psychometric intelligence scores ($p > .05$). The same was true for the associations found only in the higher psychometric intelligence group ($p > .05$).

Table 3

Pearson correlations per group for duration discrimination performance and mean gamma and theta coherence variables

	Variables	1	2	3	4	5	6	7	8	9
1	DDL (inv)	-	-.05	-.18	-.09	-.04	-.24	-.22	-.34*	-.15
2	Gamma temporal-parietal (r)	-.22	-	.63***	.63***	.93***	.28*	.21	.20	.12
3	Gamma temporal-parietal (l)	-.13	.54***	-	.92***	.70***	.18	.26	.28*	.05
4	Gamma left temporal and right parietal	.20	.63***	.87***	-	.77***	.20	.25	.29*	.08
5	Gamma right temporal and left parietal	-.24	.83***	.69***	.86***	-	.34*	.27	.28*	.22
6	Theta frontal-parietal (r)	-.10	.21	.19	.30*	.26	-	.62***	.75***	.77***
7	Theta frontal-parietal (l)	-.12	-.04	.24	.17	.09	.63***	-	.81***	.58***
8	Theta left frontal and right parietal	-.13	.11	.16	.23	.17	.79***	.84***	-	.44**
9	Theta right frontal and left parietal	-.06	.11	.28*	.20	.13	.75***	.54***	.46***	-

Note. Pearson correlations for the group with higher psychometric intelligence scores (N = 50) below the diagonal are in orange, and Pearson correlations for those with lower psychometric intelligence scores (N = 50) above the diagonal are in blue. DDL (inv) = inverted difference limen (performance measure of the duration discrimination task), so that higher values indicated a better performance, (r) = right, (l) = left. Displayed are the mean Fischer z-transformed gamma coherence values measured between temporal and parietal electrodes as well as the mean Fischer z-transformed theta coherence values measured between frontal and parietal electrodes. * $p < .05$, ** $p < .01$, *** $p < .001$.

Inferential statistics. To investigate how gamma coherence is associated with DD performance, a multiple regression analysis was conducted with the four gamma coherence variables as independent and the DD performance as dependent variables. The results showed no significant effect ($F(4, 95) = 0.63$, $p = .639$, $R^2 = .02$, $R^2_{adjusted} = -.01$). To investigate an effect in relation to psychometric intelligence, the group variable based on psychometric intelligence scores was included in the model and, in addition to the main effects, interaction effects between the group variable and the individual gamma coherence scores were also considered. The results (Table 4) showed no significant main or interaction effect. Thus, the gamma coherence variables were not associated with the DD performance, even when possible interaction effects with psychometric intelligence were considered ($F(9, 90) = 0.77$, p

= .644, R^2= .07, $R^2_{adjusted}$ = -.02).

Table 4

Results of the multiple regression analysis including intelligence group and gamma coherence variables as independent variables

	DDL			
	b [CI]	*SE*	*t*	*p*
(Intercept)	0.17 [-0.40, 0.75]	0.29	0.59	.554
Group (with higher intelligence scores)	0.19 [-0.71, 1.10]	0.46	0.43	.672
Gamma temporal-parietal (r)	0.92 [-4.00, 5.84]	2.48	0.37	.712
Gamma temporal-parietal (l)	-4.57 [-9.64, 0.50]	2.55	-1.79	.077
Gamma left temporal and right parietal	5.59 [-3.79, 14.96]	4.72	1.18	.239
Gamma right temporal and left parietal	-1.24 [-11.19, 8.70]	5.01	-0.25	.805
Group : Gamma temporal-parietal (r)	-1.40 [-7.65, 4.85]	3.15	-0.44	.658
Group : Gamma temporal-parietal (l)	5.37 [-0.92, 11.65]	3.16	1.70	.093
Group : Gamma left temporal and right parietal	-6.86 [-18.92, 5.21]	6.07	-1.13	.262
Group : Gamma right temporal and left parietal	0.09 [-12.42, 12.61]	6.30	0.02	.988
	F(9, 90) = 0.77, *p* = .644, R^2= .07, $R^2_{adjusted}$ = -.02			

Note. *N* = 100. DDL = inverted and z-standardized difference limen of duration discrimination task, (r) = right, (l) = left, Group = group based on APM scores, the group with lower intelligence scores is the reference group.

A further multiple regression analysis was performed with the four theta coherence variables as independent variables and the DD performance variable as dependent variable to investigate the association between theta coherence and DD performance. The results showed no significant effect (*F*(4, 95) = 1.32, *p* = .268, R^2= .05, $R^2_{adjusted}$ = .01). In the next step, the group variable based on psychometric intelligence was entered into the analysis. A significant main effect of theta coherence, measured between the left frontal and right parietal electrodes, was found. However, the overall model remained insignificant. When this effect was analyzed separately in a single regression analysis, thus without the interaction and the other three theta coherence variables, a significant main effect (*b*[CI] = -3.02 [-5.70, -0.34], *p* = .028), as well as a significant model could be obtained ($F(1, 98) = 4.99$, $p = .028$, $R^2 = .05$, $R^2_{adjusted} = .04$).

Table 5

Results of multiple regression analysis including intelligence group and theta coherence variables as independent variables

	DDL			
	b [CI]	*SE*	*t*	*p*
(Intercept)	0.30 [-0.68, 1.28]	0.49	0.62	.539
Group	0.05 [-1.34, 1.43]	0.70	0.07	.949
Theta frontal-parietal (r)	3.07 [-4.75, 10.88]	3.93	0.78	.438
Theta frontal-parietal (l)	4.55 [-3.84, 12.95]	4.22	1.08	.284
Theta left frontal and right parietal	-11.41 [-22.73, -0.09]	5.70	-2.00	.048*
Theta right frontal and left parietal	-2.53 [-8,58, 3.52]	3.05	-0.83	.409
Group : Theta frontal-parietal (r)	-3.81 [-15.12, 7.50]	5.69	-0.67	.505
Group: Theta frontal-parietal (l)	-5.46 [-16.71, 5.80]	5.67	-0.96	.338
Group : Theta left frontal and right parietal	11.08 [-4.10, 26.26]	7.64	1.45	.151
Group: Theta right frontal and left parietal	3.20 [-6.09, 12.49]	4.67	0.69	.495
	$F(9, 90) = 1.00$, $p = .644$, $R^2 = .09$, $R^2_{adjusted} = .00$			

Note. $N = 100$. DDL = inverted and z-standardized difference limen of duration discrimination task, (r) = right, (l) = left, Group = group based on APM scores, the group with lower intelligence scores is the reference group. * $p < .05$

As no interaction effect with the psychometric intelligence group variables was observed, in the last step, the main effects of the group intelligence, gamma coherence, and theta coherence were analyzed together in a multiple regression model. The model showed no significant main effect ($F(9, 90) = 2.70$, $p = .612$, $R^2 = .07$, $R^2_{adjusted} = -.02$). Neither theta nor gamma coherence could therefore contribute to the understanding of individual differences in temporal information processing, as depicted by DD performance.

4.4.4 Discussion

The present study aimed to investigate to what extent sensory processes, as measured by gamma coherence between temporal and parietal electrodes, and attention control, as measured by theta coherence between frontal and parietal electrodes, are associated with the performance of an auditory DD task, when measured during the encoding of this task. Furthermore, another aim was to investigate to what extent these associations differ between individuals with higher and lower psychometric intelligences. To this end, at first, the DD performance, theta, and gamma coherence were tested for group differences. The results revealed no significant differences in any of the variables between both groups. Thus, individuals with higher and lower psychometric intelligence were similar in their DD performance as well as their gamma and theta coherence during the task. The extent to which the coherence measures were associated with the DD performance measures within each group and across all participants was then examined. First, the results only showed one significant negative association in contrast to the expectations. More specifically, the theta coherence measured between left frontal and right parietal electrodes was negatively associated with performance in the DD task in the group with lower psychometric intelligence scores. Thus, individuals with lower intelligence performance showed lower theta coherence values while performing better in the DD task. Although this association pointed in the same direction in the higher intelligence group, it remained insignificant but did also not differ significantly from the one found in the group with lower psychometric intelligence scores. The correlation was then also tested across all individuals and also proved to be significantly negative. For the gamma coherence variables, no significant association with DD performance was found in either group. The subsequent multiple regression analyses also revealed no main or interaction effects in relation to gamma coherence and the intelligence group. As far as theta coherence is concerned, no main effects were found when all theta coherence variables were examined. Including the intelligence group variable then revealed a significant main effect for theta coherence (left frontal, right parietal), but no significant model. Accordingly, this theta coherence variable was examined again individually in relation to DD performance and without the intelligence group variable, revealing a small negative effect.

Before examining the links between task performance and coherence measures regarding possible group differences, it was also investigated to what extent a task-related increase or decrease could be observed during the encoding in a DD task. The results showed that neither gamma nor theta coherence increased or decreased from the prestimulus to the stimulus phase. An increase, especially in theta coherence, was expected based on previous behavioral findings showing the importance of attentional processes during temporal information task processing implementing dual-task paradigms (Brown, 2008; Brown et al., 2013; Hemmes et al., 2004). This, however, could not be shown with the present study. A difference from one of the prior studies is that they focused on a phase-based coherence measure, whereas in the present study, magnitude-squared coherence was used. Thus, it might indicate that task-related differences in temporal information processing might be more pronounced when investigating the phase parameter, which reflects the timing of an oscillation and can illustrate the degree of temporal synchronization between different areas within a frequency band. Moreover, the phase synchrony provides a measure to gather how synchronized certain areas are (Cohen, 2014). Another explanation might be that the theta and the gamma coherence was already pronounced during the prestimulus phase, as this phase might also already involve active processing and could reflect a preparatory moment. In terms of theta coherence, this would be in line with two previous studies showing that the theta coherence between frontal and parietal was already increased and could be associated with task performance (Myers et al., 2021; Sauseng et al., 2010). In this turn, it might be more indicative to relate task processing to a resting state, which would be measured independently from task processing.

Based on the TRP hypothesis, it was previously shown that individuals being more accurate and sensitive in their temporal information processing, as measured with tasks like the duration discrimination task, temporal order judgment task, or temporal generalization task, also showed higher performance in psychometric intelligence tests (Pahud et al., 2018; Rammsayer & Brandler, 2002, 2007; Troche & Rammsayer, 2009b). From this perspective, our findings of no group differences in DD performance seemed surprising. A possible explanation might lie in the characteristics of the sample. Moreover, as described above, most participants had achieved a higher educational level, which was also noticeable in the higher APM scores. This, in turn, might have attenuated the results. The limitation in the sample might also explain why there were no significant differences in theta or gamma coherence.

Previous studies showed that individual differences in sensory processing can be examined using gamma coherence (Karakaş et al., 2001; Strüber & Herrmann, 2022; von Stein & Sarntheim, 2000). So, in this context, a positive association between the gamma coherence measured between temporal and parietal electrodes and performance in the DD task was expected. The gamma coherence between these electrodes should represent the sensory process as an internal clock. Additionally, as individuals with higher psychometric intelligence also perform more accurately in tasks like the DD task (Rammsayer & Brandler, 2002, 2004), it was further expected that these associations should be higher in individuals with higher psychometric intelligence and less pronounced in those with lower psychometric intelligence. However, the results showed no significant association with any of the temporal-parietal gamma coherence variables, even if psychometric intelligence was considered. One possible reason may be that the choice of electrodes to study this sensory process related to temporal information processing was too restricted with temporal and parietal electrodes. As no previous study has investigated the performance-related association between gamma coherence and temporal information processing performance, the electrode choice was based on previous fMRI investigating the activations during temporal information processing (Grondin, 2010; Matell & Meck, 2000; Meck, 2005; Mioni, Grondin, et al., 2020). Thus, future studies with more subjects could take a more exploratory approach to the analysis in this aspect and use network analysis (Ginestet et al., 2014; Varley & Sporns, 2022). Moreover, although magnitude-squared coherence, when measured during task processing, is considered reliable (Miskovic & Keil, 2015), the reliability of the gamma frequency band has been repeatedly questioned (Popov et al., 2023). Thus, it could still be that the power values of the gamma frequency band were artificially increased, e.g., by motion artifacts, which in turn could have also influenced the magnitude-squared coherence value (Malekpour et al., 2018). However, the fact that the participants were not involved in motor processes during the encoding would argue against this. Moreover, as our study was only the second one to look at gamma coherence while processing temporal information and even the first to focus on performance-based differences, further studies are needed here.

Another reason might be that it is not only sensory processing that is reflected within the gamma frequency band but also other cognitive processes (Bonnefond & Jensen, 2015; Leicht et al., 2021). As cognitive processes are very complex, but only five frequency bands can be differentiated, it seems reasonable to expect that specific frequency bands might serve a dual-process role (Cohen, 2014). In this turn, there are also studies suggesting that the gamma frequency band involves bottom-up and top-down processing (Bonnefond & Jensen, 2015; Leicht et al., 2021). As these studies focused on prefrontal and frontal gamma effects, an additional analysis of the frontal-parietal gamma coherence was conducted. However, also this analysis showed no significant differences between the intelligence groups and no relation to DD task performance. In this sense, it must also be noted that the present study only focused on one temporal information processing task. Still, to make general statements in the sense of an internal clock mechanism (Rammsayer & Brandler, 2004, 2007), further temporal information processing tasks would have to be examined, and the extent to which similar activity patterns can be found.

Besides the investigation of ongoing sensory processes, it was also focused on how attention control is related to DD task performance and to what extent these associations differ between individuals with higher and lower psychometric intelligence. Based on previous studies (Bausenhart et al., 2016; Broadway & Engle, 2011; Ciria et al., 2019; Dyjas et al., 2012; Ogden, 2014; van Rijn, 2016) as well as the Attentional Gate Model (Block & Zakay, 1997; Zakay & Block, 1996), it was proposed that attention control in the sense of focused attention on the task should also be relevant during the encoding of temporal information processing, which in turn might also explain the relationship to psychometric intelligence. In order to measure individual differences in attention control during a task, previous studies have focused on the theta coherence between frontal and parietal electrodes (Basharpoor et al., 2021; Eschmann et al., 2020; Karakaş, 2020; Myers et al., 2021; Nurislamova et al., 2019; Sauseng et al., 2005, 2006, 2007; von Stein & Sarntheim, 2000). Based on these findings, a positive relationship between frontal-parietal theta coherence and DD task performance was expected, and that this association would be even higher for individuals with higher psychometric intelligence scores. In contrast to these expectations, only one significant but negative association with DD performance could be found. The theta coherence measured between the left frontal and right parietal electrodes was negatively correlated with DD performance. This small effect was first shown only for the group with lower intelligence scores. However, the correlation coefficients found in both groups also did not differ significantly from each other. Moreover, when this association was analyzed across all participants, also a significant negative link could be demonstrated. This indicates that, independently of psychometric intelligence, higher DD task performance was associated with lower frontal-parietal theta coherence. At first sight, it contradicts the role of attention control in task processing, as it should facilitate the processing of information (Burgoyne et al., 2023; Mashburn et al., 2020; Tsukahara et al., 2020). It further also contradicts previous findings in terms of temporal information processing (Bausenhart et al., 2016; Broadway & Engle, 2011; Ciria et al., 2019; Dyjas et al., 2012; Ogden, 2014; van Rijn, 2016) that stated in line with the Attention Gate Model (Block & Zakay, 1997; Zakay & Block, 1996) that the amount of focused attention on the task, especially during encoding should be important for temporal accuracy. One possible explanation might be that attention control is less indicative during the encoding of the first tone but more critical for the second one. As it is then, when, in parallel, the internal representation of the first tone needs to be actively maintained. This, however, is challenged by the fact that the order of the presented stimuli was randomized and thus should not have had such an effect. As the effect was relatively small and this was one of the first investigations of performance-related associations between theta coherence and DD task performance, further studies are needed to confirm this result. Moreover, it remains to be also seen to what extent this association can be replicated for other interval timing tasks.

The gamma and theta coherence variables were also investigated regarding their relationship. Based on correlational analysis, it could be seen that the coherence values of both frequency bands were positively and even significantly associated with each other in the majority of cases. Although more significant associations were found in the group with lower psychometric intelligence, these correlations did not differ significantly from those found in the group with higher psychometric intelligence. This might indicate that the chosen regions of both frequency bands were also similarly activated. In this turn, it was previously emphasized that investigating phase-amplitude coupling of two frequency bands might be more indicative of understanding individual differences in cognitive processing (Abubaker et al., 2021; Canolty & Knight, 2010; Chuderski, 2016; Cohen, 2014; Pahor & Jaušovec, 2014; Palva & Palva, 2018). Moreover, the cross-frequency phase-amplitude coupling in which the phase of a lower frequency (theta or delta) modulates the amplitude of a higher frequency (gamma) has been linked to different cognitive processes for example with working memory (for a review see Abubaker et al., 2021) with psychometric intelligence (Pahor & Jaušovec, 2014, 2016), and for delta-gamma with general fluid intelligence (Chuderski, 2016; Gągol et al., 2018). Also, a newer theoretical approach in temporal information processing research referred to as the striatal beat frequency model emphasizes the possible interplay between the phase of lower frequency bands and the amplitude of higher frequency bands (Gu et al., 2015; Wiener & Kanai, 2016). In turn, one previous study could show that the phase amplitude strength was associated with the precision in interval timing (Kononwicz et al., 2020). Although they did not measure theta and gamma but focused on alpha and beta, this might indicate that the focus of the combinations of frequency bands might be more indicative in terms of temporal processing. However, as these previous studies are limited and mostly restricted to investigating one task, further studies should focus on various tasks to draw general conclusions.

To the best of our knowledge, the present study is the first to date to investigate the association between temporal information processing performance with theta and gamma coherence in terms of individual differences while also considering differences in psychometric intelligence. To this end, it could be shown that individuals with higher psychometric intelligence did not differ in their DD task performance, theta, or gamma coherence compared to those with lower psychometric intelligence scores. Moreover, there was also no significant association between the temporal-parietal gamma coherence and the timing task performance, also not when psychometric intelligence was considered. Regarding theta coherence, it could be shown that overall higher performance in the DD task was associated with lower theta coherence measured between the left frontal and right parietal electrodes. As most previous studies were limited to task-related approaches, this study provides the first evidence for individual differences in temporal information processing by means of coherence analyses of the theta and gamma frequency bands. However, the extent to which these findings could be interpreted in the context of the TRP hypothesis requires further analyses.

5 Discussion

This dissertation aimed to strengthen and extend the TRP hypothesis using behavioral and psychophysiological measures within four studies. The two behavioral studies examined to which extent a different information processing mechanism such as spatial suppression and WM updating as a reflection of a coordination process of information processing contributes to the understanding of the TRP hypothesis. The other two studies investigated the underlying psychophysiological measures of TRP and its relationship to psychometric intelligence. The following subchapters summarize each study with the most important findings and their significance to the research question and hypotheses. The findings are then discussed and integrated into a general discussion. Then, the implications and outlook for future studies are described. The chapter ends with a conclusion.

5.1 Summary

5.1.1 Study 1

The first study aimed to replicate the relationship between TRP and psychometric intelligence and examined, to what extent spatial suppression can contribute to it. As spatial suppression is considered a bottom-up process facilitating information processing, it was expected to be positively linked to psychometric intelligence and TRP. The results showed that TRP was positively associated with psychometric intelligence in line with the expectations and previous studies (Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b). In terms of spatial suppression, it was possible to differentiate two latent variables by means of fixed-links modeling, as in a previous study (Troche et al., 2018). This fixed-links modeling approach resulted in a latent variable with constant factor loadings, reflecting, how fast individuals correctly identified the motion direction, and a latent variable with increasing factor loadings, reflecting spatial suppression. The constant latent variable showed a negative association with psychometric intelligence and TRP, indicating that individuals faster in detecting the correct motion also showed higher psychometric intelligence scores and TRP. However, contrary to our expectations, spatial suppression (varying latent variable) was also negatively associated with psychometric intelligence and TRP. When all variables were analyzed within the same model, only TRP significantly predicted individual differences in psychometric intelligence. Thus, based on these findings, only one of four hypotheses could be confirmed.

In contrast to previous findings (Arranz-Paraíso & Serrano-Pedraza, 2018; Cook et al., 2016; Melnick et al., 2013), the positive link between spatial suppression (varying latent variable) and psychometric intelligence could not be replicated. Since we implemented the same software and hardware as in the study of Melnick et al. (2013), procedural and methodological reasons for our results can be ruled out. However, since the previous studies that found a positive association were characterized by small to medium samples (N varies between 9 and 53 participants in Arranz-Paraíso & Serrano-Pedraza, 2018; Cook et al., 2016; Melnick et al., 2013), it cannot be ruled out that these effects may have been overestimated. This assumption is supported by two other recent studies that reported no significant relationship between spatial suppression and psychometric intelligence in a larger sample ($N = 177$; Troche et al., 2018) and a smaller sample ($N = 33$; Linares et al., 2020). Based on these results, a functional positive correlation seems rather unlikely. If it does exist, future studies should investigate the conditions under which the relationship occurs.

Regarding TRP, no other previous study has investigated its association with spatial suppression (varying latent variable). Both processes should reflect bottom-up mechanisms facilitating information processing (Melnick et al., 2013; Rammsayer & Brandler, 2002, 2007b; Tadin, 2015). Thus, a positive relationship between them was expected. The findings, however, revealed the opposite, indicating that higher TRP would be associated with lower spatial suppression. This contradicted previous studies, which assumed that a stronger spatial suppression effect should be associated with more efficient information processing (Arranz-Paraíso & Serrano-Pedraza, 2018; Cook et al., 2016; Melnick et al., 2013). As a possible explanation, one could assume that the small effect might be due to modality differences, as spatial suppression was investigated in terms of visual processing and TRP with auditory timing tasks in our study. However, this is contradicted by previous studies showing that TRP is not modality-bound (Haldemann et al., 2011, 2012) and should, therefore, also contribute to information processing in the visual domain. From the results it can be taken that TRP and spatial suppression are only weakly related and seem to reflect dissociable mechanisms in terms of information processing.

Besides the negative associations with spatial suppression, psychometric intelligence and TRP were negatively related to the constant variable obtained from the spatial suppression task. This variable was interpreted as the speed, at which the motion direction was correctly identified by a person and can be interpreted in terms of SIP. In turn, the negative association with psychometric intelligence can be interpreted in terms of the mental speed approach (Doebler & Scheffler, 2016; Jensen, 2006; Mashburn et al., 2023; Schubert & Frischkorn, 2020; Sheppard & Vernon, 2008) and aligns with the findings of a previous study (Troche et al., 2018). The overall model then showed that the two latent variables obtained from the spatial suppression task, namely spatial suppression (varying latent variable) and the speed of motion detection (constant latent variable), were negatively related to TRP. When all three variables were included in the model to explain psychometric intelligence, only TRP showed a significant relation. This finding confirms the first part of the TRP hypothesis (Rammsayer & Brandler, 2007) by showing that individuals with higher TRP processed their information faster, as indicated by a faster detection of the right direction of motion. Moreover, in line with previous studies (Helmbold et al., 2007; Pahud et al., 2018), TRP could explain the relationship between SIP and psychometric intelligence.

5.1.2 Study 2

Based on the findings of Study 1, the goal of Study 2 was to examine with which psychophysiological measure the internal master clock that explains differences in TRP and its relationship with psychometric intelligence can be reflected. Thus, the aim was to strengthen the understanding of the relationship between TRP and psychometric intelligence by implementing psychophysiological measures. To the best of our knowledge, this is the first time that the psychophysiological basis of the internal master clock of TRP was investigated. To this end, it was examined whether the PAF, as the psychophysiological reflection of the internal master clock, mediates the relationship between TRP and psychometric intelligence. Due to methodological differences in the recording and evaluation of previous studies examining PAF, we further examined the consistency of PAF measures by means of exploratory and confirmatory factor analyses. As in Study 1 and in line with previous findings (Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b), TRP was positively associated with psychometric intelligence. Regarding PAF, it was possible to systematically differentiate the measurements of different resting states (eyes open, eyes closed) and at different electrode sites into four latent PAF factors: PAF measured during eyes open at frontal/central electrodes, PAF measured during eyes closed at frontal/central electrodes, PAF measured during eyes open at parietal/occipital electrodes, PAF measured during eyes closed at parietal/occipital electrodes. Of these variables, only PAF measured at the frontal/central electrodes during an eyes open condition was significantly and positively associated with psychometric intelligence, indicating that individuals with a higher PAF (in Hz) at these electrode sites also showed higher psychometric intelligence. However, none of these PAF variables were associated with TRP or could mediate the relationship between TRP and psychometric intelligence. Based on these findings, only two out of four hypotheses were confirmed.

As previous studies defined PAF as a general measure of SIP (Drewes et al., 2022; Grandy et al., 2013; Hilger et al., 2022; Klimesch et al., 1996; Ociepka et al., 2022), the positive association of PAF with psychometric intelligence can be interpreted in terms of Jensen’s (1982, 2006) oscillation theory. It could be shown that individuals with higher PAF at frontal/central electrodes, reflecting the rate of neural oscillations, processed information faster and performed better in psychometric intelligence. As the correlation was limited to the frontal/central sites, it might indicate that these sites are better suited for investigating possible associations with psychometric intelligence. However, this notion seems limited because the associations between psychometric intelligence and PAF at frontal/central electrodes did not differ significantly from the ones found at parietal/occipital electrodes. As previous studies predominantly only focused on one electrode site, further studies are needed to investigate to what extent the electrode site might have an impact. The limitation to the resting state with eyes open might implicate that a certain degree of cognitive activation is needed to show associations with psychometric intelligence, which might not be given in a resting state with eyes closed (Anderson & Perone, 2018, 2023; Barry et al., 2007; Ben-Simon et al., 2008; Jann et al., 2010; Mahjoory et al., 2019). Therefore, it could be that during EO, there are already task-relevant preparatory processes or a pre-task activation present (Anderson & Perone, 2018, 2023). In line with this, previous studies have suggested an alternative interpretation of PAF as a reflection of “cognitive preparedness” (Angelakis, Lubar, Stathopoulou, et al., p. 879). Based on this, it might indicate that higher pre-task activation, as reflected in a higher PAF, might facilitate information processing and, in turn, explain higher psychometric intelligence performance.

However, this functionality of PAF is challenged by the findings in terms of temporal information processing, as only one of the TRP tasks showed a positive association with some of the PAF variables. More specifically, there was a positive correlation between the performance of the temporal generalization task and the PAF measures at parietal/occipital electrodes from the resting state with eyes open. There was no significant association for the other two timing tasks (duration discrimination and temporal order judgment tasks). There was also no relationship between TRP and any of the PAF variables on the latent level. Thus, unlike our expectations, the PAF does not seem to reflect the psychophysiological basis of the master clock. Moreover, as the performance in the TG task is accompanied by memory processes, the association between the PAF variables and TG task performance might be also caused by memory processes independent of temporal information processing. This would align with previous findings showing that PAF at parietal/occipital sites is associated with memory performance (Grandy et al., 2013; Klimesch et al., 1993; Pahor & Jaušovec, 2016; Richard Clark et al., 2004). Furthermore, it would also explain, why some previous studies that investigated the association between PAF and temporal information processing could not provide evidence for a relationship, since they focused only on timing tasks being less attenuated by memory processes (Milton & Pleydell-Pearce, 2017; Venskus & Hughes, 2021). This, however, complicates the understanding of the exact functionality of the PAF even more, as it has been previously defined as a measure of SIP (Drewes et al., 2022; Grandy et al., 2013; Hilger et al., 2022; Klimesch, 1997; Ociepka et al., 2022), then as a reflection of "cognitive preparedness" (Angelakis, Lubar, Stathopoulou, & Kounios, 2004, p. 879), and now as being sensitive to memory processes (Grandy et al., 2013; Klimesch et al., 1993; Pahor & Jaušovec, 2016; Richard Clark et al., 2004). Overall, these findings show that the PAF seems to be involved in the efficiency of information processing. However, as the alpha frequency band itself reflects different cognitive roles, it might also explain why the PAF cannot be linked to one specific aspect (Ociepka et al., 2022). Further studies are needed to clarify the functionality of the PAF. Although we were unable to provide evidence that the PAF reflects the psychophysiological basis of the master internal clock, the study was the first to investigate the possible psychophysiological basis of TRP.

5.1.3 Study 3

The third study aimed to replicate the relationship between psychometric intelligence and TRP found in studies 1 and 2. It also aimed to investigate further the second aspect of the TRP hypothesis, which states that individuals with higher TRP also coordinate their mental operations better, leading to higher scores in psychometric intelligence tests. In order to extend previous studies, we investigated the coordination aspect by means of WM updating. The results showed, as in studies 1 and 2, a positive relationship between TRP and psychometric intelligence. It could be further demonstrated that TRP and psychometric intelligence were each positively linked to WM updating. The final mediation model revealed that WM updating partially mediated the relationship between TRP and psychometric intelligence, which was interpreted as that higher TRP facilitates WM updating, leading to higher psychometric intelligence scores. Based on these findings, all of our hypotheses could be confirmed.

The results of the partial mediation analysis are consistent with the second part of the TRP hypothesis (Rammsayer & Brandler, 2007). As this second part has only been investigated once before (Troche & Rammsayer, 2009b), Study 3 marks the second study to date to examine this relation. In contrast to Troche and Rammsayer (2009b), the coordination aspect was chosen to be investigated with a more specific WM measure, namely WM updating. In line with the TRP hypothesis, it could be shown that WM updating partially mediated the relationship between TRP and psychometric intelligence, suggesting that TRP might facilitate the process of WM updating, resulting in fewer errors in information processing and, through this, also in better performance in psychometric intelligence tests. This can also be interpreted in terms of the binding hypothesis, which indicates that individuals with higher TRP might be better at forming and detaching from bindings in a more temporally precise way, leading to better WM updating performance (Chuderski, 2019; Oberauer, 2005, 2019). As this facilitates information processing, it can, in turn, explain why these individuals also perform better in a psychometric intelligence test.

However, opposing views argue that the relationship between TRP or sensory discrimination ability and psychometric intelligence is not due to differences in sensory acuity but is related to common WM processes. In this context, Jastrębzski et al. (2021) showed that, as in Troche and Rammsayer (2009b), the relationship between temporal sensory discrimination and psychometric intelligence was fully explained by WMC. However, in contrast to Troche and Rammsayer (2009b), they argued that higher WMC should lead to higher temporal acuity and, thus, higher psychometric intelligence. They, therefore, argued that it is not the differences in sensory acuity but the ones regarding WMC that explain the relationship between TRP and psychometric intelligence. Thus, both studies support a different causal direction. However, since both studies, as well as the present study, are based on latent regression analyses, it is not possible to decide which causal direction might be the right one. A striking fact in the previous studies (Jastrzębski et al., 2021; Troche & Rammsayer, 2009b) is that the implemented WMC variable was very closely linked to psychometric intelligence, which makes it difficult to distinguish between these constructs and, therefore, it may also have had an impact on the mediation analyses. This could be circumvented in the present study by focusing on a more specific process of WM. However, it should be noted that only one task was used to assess WM updating in the present study. Future studies should focus on a more pronounced measurement of WM updating by implementing multiple tasks.

5.1.4 Study 4

Based on the findings of Studies 2 and 3, Study 4 aimed to investigate to what extent sensory processes, as measured with the gamma coherence between temporal and parietal electrodes during the encoding of temporal information, and attention control, as measured with theta coherence between frontal and parietal electrodes during the encoding of temporal information, can contribute to the understanding of individual differences in temporal accuracy. Moreover, it was investigated how these associations differ in terms of higher and lower psychometric intelligence. The results showed no significant association between DD performance and gamma coherence, also not when different levels of psychometric intelligence were considered. Regarding theta, a negative association could be shown for theta coherence measured between left frontal and right parietal electrodes and temporal accuracy. Thus, individuals with a higher temporal accuracy showed a lower theta coherence between left frontal and right parietal electrodes. This association did not differ in terms of psychometric intelligence. Thus, none of the hypotheses could be confirmed.

Surprisingly, temporal accuracy and temporal-parietal gamma, indicating sensory processing, as well as the frontal-parietal theta coherence, indicating attention control, did not differ in terms of psychometric intelligence. A possible explanation might lie in the characteristics of the sample, as it mainly consisted of students having a relatively high educational level. This might have attenuated the data.

Regarding the gamma coherence, surprisingly there could be found no association with temporal information processing performance which should be associated with a sensory process, although previous studies could show gamma coherence to be associated with individual differences in sensory processing (Karakaş et al., 2001; Strüber & Herrmann, 2022; von Stein & Sarntheim, 2000). One possible explanation might lie in the electrode selection, as the study focused on the gamma coherence between temporal and parietal electrodes. However, as previously suggested, the possible mechanism of an internal clock might not be linked to only one or two areas but may involve even more. In this turn, a network analysis in future studies might be more indicative. Besides the electrode selection, gamma as a frequency band itself has been shown to be less reliable (Popov et al., 2023). Also, possible artifacts (e.g., muscle artifacts, motoric) might have affected the gamma coherence and influenced the coherence measures, as power decreases and increases can affect magnitude-squared coherence (Malekpour et al., 2018). Although intensive raw data inspection was conducted twice before calculating the coherence analysis, some artifacts might have been unconsidered. A possibility to minimize that might be to focus in further studies on the phase-based coherence, as this is less affected by these artifacts (Alam et al., 2020; Morales & Bowers, 2022). Moreover, it has also been shown that phase-based coherence is more sensitive to the synchronized neural activity related to the stimulus than when it is power based (Ding & Simon, 2013).

Regarding the theta coherence, an unexpected negative association could be shown between temporal accuracy and theta coherence (left frontal, right parietal). As differences in theta coherence should have reflected attention control, which is considered to facilitate information processing (Burgoyne et al., 2023; Mashburn et al., 2020; Tsukahara et al., 2020), this would contradict this notion. More specifically, the finding indicates that individuals with lower attention control, indexed by lower theta coherence between left frontal and right parietal electrodes, showed a higher temporal accuracy performance. One possible explanation might be that attention control is less important during the encoding process and becomes evident during the encoding of the comparison tone. However, as in the standard and comparison tones, they were randomly interleaved, such an explanation seems challenged. From this perspective, it might be important to investigate further, if there are differences in terms of presented order. Moreover, it could also be that differences in a sensory process such as the rate of an internal clock are still more important to explain higher temporal accuracy (Rammsayer & Brandler, 2004). However, as in Study 4, the temporal-parietal gamma coherence, which was predicted to reflects these sensory based differences, not associated with temporal accuracy, also this notion has to be investigated further. From this perspective, it might be important to investigate further, if there are differences in terms of presented order.

5.2 General Discussion

The TRP hypothesis postulates that individuals who show higher temporal accuracy and sensitivity also process their information faster and coordinate their mental operations better, leading to a higher performance in psychometric intelligence tests (Rammsayer & Brandler, 2002, 2007). The presented four studies could provide new insights into the behavioral and psychophysiological aspects of this hypothesis. In line with the first aspect of the TRP hypothesis, it could be shown that individuals with a higher temporal accuracy also processed information faster, as indicated by their faster detection of the motion direction. Regarding the second part of the hypothesis, it could also be shown that they showed a higher accuracy within a WM updating task, indicating they have a better coordination of their mental operations, which in turn also led to a higher performance on psychometric intelligence tests. As the differences in TRP should be reflected by an internal master clock in the form of neural oscillations, it was further investigated, if specific EEG analysis as could help understand this process. Hereby a frequency analysis was used for the investigation during a resting state and coherence analyses for the focus on activity during the task. However, no relation could be shown. The findings of these two behavioral and two psychophysiological studies are discussed and integrated in the following.

5.2.1 Support of the TRP Hypothesis on the Behavioral Level

Studies 1-3 could uniformly confirm a positive relationship between TRP and psychometric intelligence. In all three studies, TRP contributed significantly to the understanding of individual differences in psychometric intelligence by explaining 33 % (Study 1), 31 % (Study 2), and 36 % (Study 3) of its variance. These findings were comparable with previous studies, showing 36 % (Pahud et al., 2018) to 41 % of the variance explained by TRP in psychometric intelligence (Helmbold et al., 2007).

Furthermore, it was also possible to confirm the TRP hypothesis in terms of SIP as well as the coordination process of mental operations. In line with these findings, it could be shown that individuals with higher TRP detected the motion direction faster, which can also be interpreted in terms of faster information processing (Study 1), and showed better WM updating (Study 3), reflecting a better coordination of mental operations, and thus higher psychometric intelligence. Moreover, TRP could be seen as a more important psychometric intelligence predictor than spatial suppression as well as the motion detection speed, in line with previous findings showing TRP to be more important than SIP (Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007). Thus, as in previous studies (Helmbold et al., 2007; Pahud et al., 2018), the relationship between SIP and psychometric intelligence could be explained in terms of TRP. This underlines the importance of TRP as a fine-tuning capacity, reflecting a substantial predictor of psychometric intelligence (Pahud et al., 2018; Rammsayer & Brandler, 2007). In terms of the evidence of the second part, it could be further shown that TRP also leads to better WM updating, which in turn also facilitates the information process as fewer errors occur. Thus, both studies could confirm the notions of the TRP hypothesis and underline its importance in predicting individual differences in psychometric intelligence.

Regarding the theoretical framework, the association between SIP and psychometric intelligence in Study 1 and between WM updating and psychometric intelligence in Study 3 can also be interpreted in terms of Jensen’s oscillation model (1982, 2006). When further combined with the found associations of TRP, it was seen that, based on the extended notion by Rammsayer and Brandler (2007; based on Surwillo, 1968), individuals differing in their temporal acuity and temporal sensitivity not only process information faster but also coordinate their mental operations better, which in turn could explain intelligence differences. However, as Jensen (1982, 2006) outlines in his theory, SIP and WM processes might also work together in the sense that higher SIP should enable better WM processing. In line with this, previous studies showed that both were important separate predictors of psychometric intelligence (for a review, see Frischkorn et al., 2022) but also contribute together to the understanding of individual differences in psychometric intelligence (Dang et al., 2015;

Frischkorn et al., 2019). As both are also implemented within the TRP hypothesis, the next important step might be to investigate how these paths align. Nevertheless, it could be shown in all of the three studies that TRP reflects a general process that leads to faster information processing and facilitates an effective coordination of information processing which in turn then also explain differences in psychometric intelligence.

5.2.2 Arriving at a Broader Understanding of TRP by the Use of Psychophysiological Correlates

While studies 1-3 have made an important contribution to understanding the relationship between TRP and psychometric intelligence, and could confirm previous results, it remains unclear, to what extent differences in TRP, as indicated by an internal master clock, are reflected in the rate of neural oscillations (Rammsayer & Brandler, 2007; Surwillo, 1968). This question was investigated then by studies 2 and 4. Whereas Study 2 focused on frequency differences of the PAF measured during a resting state before temporal information processing tasks, Study 4 focused on how different brain areas communicate during task processing by means of gamma and theta coherence as a reflection of sensory processing and attention control. In both studies, no significant contribution could be made to the psychophysiological understanding of individual differences in temporal information processing. Neither the PAF measured during the resting state, nor the temporal-parietal gamma coherence could contribute to the understanding of the internal master clock. Possible reasons might lie in how the PAF was measured. So, the PAF was only assessed during the resting state and not during a task, but, in turn, measured at 64 electrodes during six measurement points, from which four latent variables were derived. Nevertheless, neither of these variables could be associated with TRP. As the role of PAF seems complex (Ociepka et al., 2022), we further wanted to focus on other frequency bands in order to overcome the limitation of the resting state. As previous studies have shown that the complexity of specific cognitive processes cannot be reflected by merely focusing on the power within one frequency band at specific electrodes (Bowyer, 2016; Decker et al., 2017), the EEG analyses were adapted by focusing on coherence analyses and thus the synchronization between electrodes. However, in contrast to Study 2, it was only focused on two areas, temporal and parietal. Although these areas were chosen based on previous studies (Matell & Meck, 2000; Meck, 2005; Nani et al., 2019), it might have also been too limited. Thus, as it seems clear that the PAF does not reflect a possible master clock in terms of gamma coherence, more research is needed.

Besides investigating how PAF is related to TRP, also its relationship with psychometric intelligence was examined. In Study 2, a positive association between the PAF measured during the resting state with eyes open at frontal/central electrodes and psychometric intelligence could be observed. This result was in line with previous studies (Angelakis, Lubar, Stathopoulou, et al., 2004; Pahor & Jaušovec, 2016) and could be interpreted in terms of Jensen’s (1982, 2006) oscillation theory indicating that individuals with higher PAF, which might have indicated a faster SIP, also performed better in psychometric intelligence tests. However, in contrast to previous studies (Basten et al., 2015; Basten & Fiebach, 2021; Jaušovec & Jaušovec, 2005; Lee et al., 2012) and expectations, the coherence measures could not provide insight into the different information processing in psychometric intelligence. A possible explanation might lie in the composition of the participants. More specifically, primarily students were implemented in Study 4, which might have led to less variability within the sample.

One possible explanation for these findings of no associations in terms of PAF and TRP, in regard of the gamma coherence and temporal accuracy and its relationship to psychometric intelligence might be that both studies implemented power-based frequency parameters. Even though in Study 2 the PAF in Hz was analyzed in terms of individual differences, it was still the point with the highest power in the alpha frequency band (Jann et al., 2012). In Study 4, the coherence values of theta and gamma were based on the magnitude-squared coherence, which can be influenced by power increases or decreases (Cohen, 2014; Malekpour et al., 2018). Therefore, it might be that power cannot reflect what either Jensen or Surwillo meant by the rate of neural oscillations. Another parameter that can be extracted from the EEG and is independent of power is the phase parameter, which reflects the timing of the neural oscillations (Cohen, 2014). This phase parameter might be interesting when also investigating higher frequency bands such as gamma since their power can be attenuated by possible muscle or other high frequency artifacts, which might be less reflected within the phase (Alam et al., 2020; Morales & Bowers, 2022; for a review, see Muthukumaraswamy, 2013). Phase-based coherence can be interpreted in this turn, that when different electrodes are synchronous in their phase, it indicates that their neurons are firing at the same time in a synchronized manner (Cohen, 2014; Ding & Simon, 2013). Thus, the brain’s activity might be more organized, facilitating information processing which in turn leads to higher efficiency. However, as it still remains unclear to what extent power- or phase-based coherence measures similarly (Cohen & Gulbinaite, 2014), it might also be useful to investigate both measures within one study in the future.

5.2.3 Integrating the Behavioral and Psychophysiological Findings Regarding the First Part of the TRP Hypothesis

As Study 1 could provide substantial evidence for the positive relationship between TRP and psychometric intelligence, Study 2 aimed to investigate the underlying process of the internal master clock, which could lead to differences in TRP. The theoretical frameworks of Jensen (1982, 2006), as well as of Rammsayer and Brandler (2002, 2007) and Surwillo (1968), suggested that the rate of neural oscillations might be crucial in understanding individual differences in psychometric intelligence. Focusing on a measure that implied speed differences in psychophysiological content seemed even more intriguing. In this turn, the PAF was chosen. More so, since the PAF has also been defined as a neurocognitive measure of SIP, from this perspective, the investigation of Study 2 also contributes to the understanding of the first aspect of the TRP hypothesis. However, as seen before, the results showed that although one PAF variable was associated with psychometric intelligence, there was no significant link to TRP. Thus, even if the association between PAF and psychometric intelligence might be interpreted in terms of Jensen (1982, 2006) and thus as an explanation between SIP and psychometric intelligence, it is still questionable why no association could be found with TRP. From this perspective, it remains to be seen which specific psychophysiological measures of the internal master clock can be assessed to then understand, why TRP leads to faster SIP and higher psychometric intelligence.

5.2.4 Integrating the Behavioral and Psychophysiological Findings Regarding the Second Part of the TRP Hypothesis

The second part of the TRP hypothesis focuses on how mental operations are more effectively coordinated through higher TRP, which, in turn, also allows for higher psychometric intelligence (Rammsayer & Brandler, 2007). In line with this part of the TRP hypothesis (Rammsayer & Brandler, 2007), Study 3 could show that WM updating, as a reflection of this coordination aspect, partially mediated the relationship between TRP and psychometric intelligence. This finding was interpreted as TRP (possibly) facilitating WM updating, leading to fewer errors and higher psychometric intelligence. From this perspective, Study 3 could show that the relationship between timing accuracy and sensitivity with psychometric intelligence is due to a genuine sensory relationship. This contrasts with previous findings showing that the link between TRP, or sensory discrimination ability, and psychometric intelligence can be explained entirely by WMC (Jastrzębski et al., 2021; Troche et al., 2014; Troche & Rammsayer, 2009b). Based on these findings, it was further shown that the relationship between sensory discrimination ability and WMC, as well as between sensory discrimination ability and psychometric intelligence, could be explained by attention control (Tsukahara et al., 2020). This would indicate that the relationship between general sensory discrimination ability and psychometric intelligence is not due to individual differences in a bottom-up process, such as sensory processing, but instead due to individual differences in a top-down process, such as attention control. Thus, these findings contrast with the notion of the TRP hypothesis as they would argue against a significant role of the internal master clock. To further inspect to what extent involved bottom-up as well as top-down processes might explain why individuals with higher temporal accuracy are also better in psychometric intelligence tests, it was focused on the EEG activity during a TRP task in Study 4 by means of coherence analyses. However, as mentioned before, there was no functional relationship between temporal accuracy and the coherence measure that was supposed to reflect individual differences in sensory processing. Moreover, there were no differences in psychometric intelligence, which might further limit possible interpretations. Surprisingly, it could be shown that theta coherence, as a reflection of attention control, when measured between left frontal and right parietal electrode sites was (weakly) negatively related to temporal accuracy. From a first viewpoint, this might be an indication that attention control might, after all, not be so relevant during temporal information processing tasks and might be interpreted in terms of the TRP hypothesis. However, as there were also no significant differences in the temporal information processing performance in terms of psychometric intelligence as well as in the measure supposed to reflect an internal clock, this notion seems limited, and further studies are needed.

5.3 Implications and Outlook

With the present dissertation, a step further was taken to understand individual differences in psychometric intelligence, both on a behavioral and a psychophysiological level. We have also come closer to understanding how the internal (master) clock manifests itself in the brain and how psychophysiological measures can contribute to understanding individual differences in psychometric intelligence. These findings provide good starting points for future studies, which will be discussed in the following.

Besides behavioral aspects, possible psychophysiological characteristics of the TRP hypothesis were also investigated. Although Studies 2 and 4 could not uncover the psychophysiological basis of the internal master clock, they did provide essential contributions to previous research. For example, the systematic investigation of the PAF, when measured during resting state, showed that this measure should be redefined, and the findings indicated that the alpha frequency measure is not suitable for investigating individual differences in temporal information processing. This, in turn, led to Study 4, in which the ongoing sensory processes were examined by means of gamma coherence. Moreover, it was also tested to what extent individuals differ on the impact of involved top-down processes such as attention control with the frontoparietal theta coherence during task processing and to what extent this is associated with psychometric intelligence differences. Since no indicative correlations were found there either, it may be, as already discussed above, that it is not a power-based measure but possibly the phase that would further indicate the timing of the neural oscillations (Cohen, 2014; van Wassenhove et al., 2019). Besides focusing only on separate frequency bands, it might also be the interaction of different frequency bands. In this turn, it was previously emphasized that investigating phase-amplitude coupling of two frequency bands might be more indicative of understanding cognitive processing (Abubaker et al., 2021; Canolty & Knight, 2010; Chuderski, 2016; Cohen, 2014; Pahor & Jaušovec, 2014; Palva & Palva, 2018). More so, it has been shown that the cross-frequency phase-amplitude coupling between theta-gamma was associated with psychometric intelligence (Pahor & Jaušovec, 2014, 2016) and delta-gamma with general fluid intelligence (Chuderski, 2016; Gągol et al., 2018), and even recently with the precision in interval timing (Kononwicz et al., 2020). This might indicate that the cross-frequency coupling might be more indicative of investigating differences in TRP and its relationship to psychometric intelligence.

The findings of Studies 1-3, in addition to previous results (Haldemann et al., 2012; Helmbold et al., 2007; Pahud et al., 2018; Rammsayer & Brandler, 2007; Troche & Rammsayer, 2009b), show that TRP is a substantial predictor of psychometric intelligence in young and healthy adults. While the relationship between TRP and psychometric intelligence is shown to be very substantial, less is known about how it behaves in healthy elderly adults. Previous studies focusing on aging effects on temporal information processing suggest that, in addition to the processing speed, the performance in temporal information processing decreases with age (Block et al., 1998; Mioni, Capizzi, et al., 2020; Paraskevoudi et al., 2018; Rammsayer et al., 1993; Turgeon et al., 2016; Von Krause et al., 2022). Also, regarding psychometric intelligence, it has been shown that with aging, a decline in nonverbal compared to verbal abilities can be observed (for a review, see Lindenberger & Baltes, 1994; Sánchez-Izquierdo & Fernández-Ballesteros, 2021; Zihl & Reppermund, 2023). However, as these studies are mostly limited to cross-sectional and between-subjects design, in which younger adults are compared to older adults, it might be more interesting to see to what extent individual differences in information processing mechanisms can be found within older adults and how they can be related to psychometric intelligence. This would allow age-related cognitive strengths and challenges to be better identified and understood, which could also help develop accurate assessments to test cognitive performance in old age.

5.4 Conclusion

In summary, the relationship between TRP and psychometric intelligence could be examined in more detail in four studies with the present dissertation. To this end, the relationship between TRP and psychometric was successfully replicated in three independent studies (1-3). In addition, the TRP hypothesis was confirmed concerning its relation to SIP (Study 1) and coordination of mental operations (Study 3). These behavioral findings were extended by examining the psychophysiological basis of TRP differences for the first time using EEG frequency and coherence analyses (Studies 2 and 4). No functional correlations were found, but as this is the first study investigating the psychophysiological basis of TRP, important starting points for further studies can be derived from these findings. Overall, the results contribute to the understanding of individual differences in psychometric intelligence by repeatedly showing, what an important predictor TRP is and providing first insights into its psychophysiological basis.

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