Spatiotemporal Interference Effects: A Bayesian Model-Based Explanation

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Abstract

Spatiotemporal interference effects refer to illusory phenomena wherein temporal perception is disturbed by spatial information or spatial perception is disturbed by temporal information. Some studies contend that spatiotemporal interference is asymmetrical, with spatial interference on time consistently being more pronounced. Other research suggests that the magnitude of mutual interference between time and space is modulated by experimental factors; generally, spatial interference on time is greater, yet time can also exert interference on space to an equivalent or even greater degree. Following a review of the principal tenets of Metaphor Theory and Magnitude Theory, this paper focuses on analyzing the Bayesian model' s account of spatiotemporal interference effects, and concludes by proposing three directions for future research: expanding the explanatory scope of the Bayesian model regarding spatiotemporal interference effects, elucidating the neural mechanisms underlying spatiotemporal interference based on Bayesian inference, and exploring methods for modulating spatiotemporal interference.

Full Text

Spatiotemporal Interference Effect: An Explanation Based on Bayesian Models

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Abstract

The spatiotemporal interference effect refers to the phenomenon where temporal perception is disturbed by spatial information or spatial perception is disturbed by temporal information, resulting in illusions. Some studies suggest that spatiotemporal interference is asymmetric, with spatial interference on time always being greater. Other research indicates that the strength of mutual interference between time and space is influenced by experimental factors. In general, spatial interference on time is greater, but time can also produce interference on space of equal or even greater magnitude. After briefly reviewing the main ideas of metaphor theory and A Theory of Magnitude (ATOM), this paper focuses on analyzing the explanation of spatiotemporal interference effects from Bayesian models. Finally, three issues for future research are proposed: expanding the scope of Bayesian models to explain spatiotemporal interference effects, exploring the neural mechanisms of spatiotemporal interference based on Bayesian inference, and seeking methods to regulate spatiotemporal interference.

Keywords: spatiotemporal interference effect, Bayesian model, A Theory of Magnitude, metaphor theory

In ball sports, scoring depends on hitting the ball at the right time and in the right position. Time and space are closely linked in human movement and indeed in all aspects of life (Cona et al., 2021), and they can mutually influence each other (Cai et al., 2018). The Kappa effect (Cohen et al., 1953) and the Tau effect (Helson, 1930) are two widely observed spatiotemporal interference phenomena. The former refers to temporal perception[1] being disturbed by spatial information, while the latter refers to spatial perception being disturbed by temporal information.

In classic studies of these two effects, horizontally arranged light bulbs flash sequentially. The perceived time interval (or duration) between bulb illuminations increases as the distance between bulbs increases—this is the Kappa effect. Conversely, the perceived distance between bulbs increases as the time interval between illuminations increases—this is the Tau effect. Similar spatiotemporal interference effects have been discovered in subsequent research. For example, perceived time increases with the length of presented lines (Magnani et al., 2014; Starr & Brannon, 2016) and with the area of disks or squares (Rammsayer & Verner, 2014, 2015). Perceived distance increases with the presentation duration of lines (Homma & Ashida, 2019), the duration of pure tones (Kranjec et al., 2019), and the temporal interval between two tactile points on the skin (Goldreich, 2007; Goldreich & Tong, 2013).

Although several reviews have introduced related research (Choy & Cheung, 2017; Loeffler et al., 2018; Winter et al., 2015; 毕翠华, 黄希庭, 2011; 陈亚林, 刘昌, 2013), they all explained the mechanisms of spatiotemporal interference effects from the perspectives of metaphor theory (Boroditsky, 2000) and A Theory of Magnitude (Walsh, 2003). In recent years, researchers have applied Bayesian models to the field of spatiotemporal interference effects (Cai et al., 2018; Chen et al., 2021; Chen et al., 2016; Goldreich, 2007; Goldreich & Tong, 2013; Lambrechts et al., 2013; Martin et al., 2017), yet no article has systematically reviewed these studies. Therefore, summarizing and discussing the Bayesian perspective on spatiotemporal interference effects is essential. This paper first reviews recent research related to spatiotemporal interference effects, then revisits the main ideas of metaphor theory and A Theory of Magnitude, subsequently introduces the new explanations provided by Bayesian models for spatiotemporal interference effects, and finally analyzes the relationships among the three theories and issues requiring attention in future research, laying a foundation for revealing the cognitive and neural mechanisms of spatiotemporal interference.

[1]Temporal perception primarily includes duration perception and temporal order perception. Duration refers to the perceived length of time between events or the duration of an event, while temporal order refers to the sequential characteristics of time. In the spatiotemporal interference effect studies described in this paper, temporal perception is only related to duration perception and not to temporal order perception.

Spatiotemporal Interference Effect Research

Many studies suggest that spatiotemporal interference is asymmetric[1], with spatial information interfering with temporal perception while temporal information either does not interfere with spatial perception or does so only minimally. For example, Casasanto and Boroditsky (2008) designed six spatiotemporal interference experiments using gradually lengthening lines (Experiments 1-4), static line length (Experiment 6), and moving dot distance (Experiment 5) as spatial distance information, while using the presentation duration of lines or dots (Experiments 1-6) and the duration of audio presented synchronously with visual stimuli (Experiment 4) as temporal duration information. They found that in all experiments, when the presentation duration of lines or dots was fixed, participants' perceived duration increased with distance, but conversely, perceived distance was not affected by changes in duration. This indicates that spatial interference on time is stronger. Subsequently, Casasanto and colleagues (Bottini & Casasanto, 2013; Casasanto et al., 2010) used the duration and distance of two cartoon snails moving in parallel in a video as temporal and spatial information. Children in the experiment needed to randomly compare which snail moved longer in duration or distance. The study found that when the two snails moved for the same duration, children tended to believe that the snail moving a longer distance also moved for a longer time. However, when the two snails moved the same distance, children's judgments of moving distance were minimally affected by movement duration. Statistical results showed that spatial interference on time was greater than temporal interference on space. Later researchers obtained similar results using gradually growing or static line lengths (Magnani et al., 2014; Merritt et al., 2010; Starr & Brannon, 2016) and distances formed by horizontally flashing dots (Reali et al., 2019) as spatial information, finding that longer distances led to longer perceived durations while temporal information had no or minimal effect on perceived distance.

Other studies have found that time can also interfere with space to an equal or even greater degree. For example, Riemer et al. (2018) investigated spatiotemporal interference in a simulated virtual environment and found that when using the length of gradually growing curves and their presentation duration as spatial and temporal information—where both types of information originated from the curve' s growth motion—longer curve lengths led to longer perceived durations, with spatial interference on time being greater. However, when using virtual room size and presentation duration as spatial and temporal information—where the sources of spatiotemporal information were independent—larger rooms led to longer perceived durations, and longer presentation durations also led to larger perceived room sizes, with equivalent degrees of spatiotemporal interference. In this study, different sources of spatiotemporal information were important factors influencing the strength of bidirectional interference. Homma and Ashida (2015, 2019) used changing line lengths and presentation durations as spatial and temporal information. They found that when the differences between levels of line presentation duration were smaller than the differences between levels of line length, temporal stimulus saliency (discriminability) was low, longer line lengths led to longer perceived time, and spatial interference on time was stronger (Homma & Ashida, 2015). Conversely, when they reduced the differences between levels of line length to make spatial stimuli harder to discriminate, line presentation duration produced stronger interference on perceived length (Homma & Ashida, 2019). Thus, the dimension with lower stimulus saliency is more easily influenced by the dimension with higher stimulus saliency. Additionally, research has found that presenting stimuli through different sensory modalities affects spatiotemporal perceptual acuity. Spatial perceptual acuity is highest when information is obtained visually and lower when obtained auditorily or tactilely, while temporal perceptual acuity is higher when information is obtained auditorily and lower when obtained visually (Amadeo et al., 2019; Cai & Connell, 2015). Loeffler et al. (2018) reviewed 16 studies related to spatiotemporal interference effects and proposed that studies finding stronger spatial interference on time mostly used vision to obtain both spatial and temporal information, while studies finding symmetric spatiotemporal interference mostly used audition for temporal information and vision or touch for spatial information. The dimension with higher perceptual acuity can produce greater interference on the other dimension (Cai & Connell, 2015; Cai et al., 2018). In summary, the strength of bidirectional interference between time and space is modulated by certain factors in experimental tasks, such as the source of spatiotemporal information, stimulus saliency, and perceptual acuity.

In conclusion, there is still controversy regarding the direction and strength of spatiotemporal interference effects. Relevant studies have simultaneously found phenomena where spatial interference on time is greater, temporal interference on space is greater, and time and space interfere with each other to equal degrees. Reasonable theories are needed to explain these phenomena and the mechanisms underlying spatiotemporal interference effects.

[1]In mathematics, physics, psychology, and other disciplines, "asymmetry" and "symmetry" have specific mathematical and semantic meanings. In psychological research on spatiotemporal interference effects, "asymmetry" is widely used to describe phenomena where one dimension (time or space) produces greater interference on the other dimension, while "symmetry" is commonly used to describe phenomena where space and time produce bidirectional interference of

equal magnitude.

Metaphor Theory

Metaphor Theory explains spatiotemporal interference effects from the perspective of the relationship between abstract and concrete concepts. Metaphor Theory (Boroditsky, 2000) proposes that people can directly obtain spatial information through vision and other senses but cannot directly obtain temporal information. Time is more abstract than space, and in daily life people have a tendency to use concrete spatial information as metaphors for abstract temporal information, such as "March is in front of April" or "a long vacation." The asymmetry of spatiotemporal interference is widespread in language, where using space to metaphorically express time is far more common than using time to express space (Loeffler et al., 2018). Proponents of Metaphor Theory argue that people think about time through space, causing the asymmetric relationship of spatiotemporal interference in language to extend to the perceptual domain, thereby producing asymmetric spatiotemporal interference effects (Casasanto & Boroditsky, 2008). Since animals do not use language and do not think about time using spatial metaphors, animals' spatiotemporal interference effects are symmetric (Merritt et al., 2010; 毕翠华, 黄希庭, 2011).

Recent research does not fully support Metaphor Theory. While Metaphor Theory can explain the phenomenon of asymmetric spatial interference on time, multiple studies with human participants have found stronger temporal interference on space (Cai & Connell, 2015; Homma & Ashida, 2019; Kranjec et al., 2019), which contradicts Metaphor Theory' s claim that spatial interference on time is always stronger (Cai et al., 2018).

A Theory of Magnitude (ATOM)

A Theory of Magnitude (ATOM) explains spatiotemporal interference effects from the perspective of magnitude representation. Proposed by Walsh (2003), ATOM 主张 that time, space (and number) information is processed in a common magnitude system. Brain imaging (Cona et al., 2021; Skagerlund et al., 2016), EEG (Cui et al., 2022), and transcranial magnetic stimulation (Riemer et al., 2016) studies have revealed overlapping brain regions (especially in the parietal cortex) involved in processing temporal and spatial information, providing neurobiological evidence for the magnitude system. In this system, temporal and spatial information share a unified magnitude representation, and processing information in one dimension affects processing in the other dimension, thereby producing spatiotemporal interference effects. Although many researchers believe ATOM predicts symmetric spatiotemporal interference effects (Bottini & Casasanto, 2013; Casasanto et al., 2010; Loeffler et al., 2018; Merritt et al., 2010; 陈亚林, 刘昌, 2013), Walsh and colleagues argue that interference between dimensions in the magnitude system is not necessarily symmetric (Bueti & Walsh, 2009; Lambrechts et al., 2013). They reviewed fMRI studies related to temporal and spatial processing and found that different temporal or spatial tasks activated different cortical sites, implying that the brain tissue involved in different temporal or spatial tasks differs, and that the strength of spatiotemporal interference may be influenced by experimental tasks (Bueti & Walsh, 2009).

Researchers have further developed ATOM from a Bayesian inference perspective. In the common magnitude system, the integration and estimation of temporal and spatial magnitudes are achieved through Bayesian inference (Lambrechts et al., 2013; Martin et al., 2017), with details introduced in the next section.

Bayesian Models of Spatiotemporal Perception

Bayesian inference describes how individuals combine known information (the prior) with new information (the likelihood) to make optimal decisions (the posterior). Taking temporal perception as an example, for a given duration, the prior refers to an individual' s knowledge and experience about duration length from previous experiences, the likelihood refers to the probability distribution of duration generated when duration information enters the brain through sensory input, which can be regarded as the sensory memory representation of duration (Chen et al., 2016), and the posterior refers to the probability distribution of duration information formed after integrating the prior and likelihood, with the perceived duration length being the individual' s optimal estimate of the posterior. Körding and Wolpert (2006) proposed that the central nervous system experiences noise when receiving signals from sensory and motor systems, and that Bayesian inference integrating prior knowledge and likelihood may be a fundamental element of human perceptual processing. In recent years, researchers have applied Bayesian inference theory to the field of spatiotemporal interference effects, reinterpreting and developing classic models in this domain.

Constant Velocity Bayesian Model

The constant velocity model is based on the constant velocity assumption, which has received support from many studies in temporal perception (Collyer, 1976; Henry & McAuley, 2013; Huang & Jones, 1982). This assumption states that most moving objects in daily life move at a constant velocity. Based on this life experience, observers perceive independent stimuli appearing at different spatial locations at temporal intervals in Kappa and Tau effect studies as the same object moving at constant velocity (Chen et al., 2016). Jones and Huang (1982) first proposed an algebraic model, later called the classic model or constant velocity model, to quantitatively explain the Kappa and Tau effects. In the constant velocity model explaining the Kappa effect, the perceived duration te is a weighted average of the physical duration ts and the expected duration, where the expected duration is the ratio of actual distance to constant velocity, i.e., . The algebraic expression of this model is $=\quad + (1 - \quad)$. From this, it can be seen that when the weight ω of physical duration is smaller, the perceived duration depends more on the expected duration (is more influenced by spatial distance), meaning the Kappa effect is stronger. Similarly, in the constant velocity model explaining the Tau effect, the perceived distance is a weighted average of physical distance and expected distance, where expected distance is the product of physical duration and constant velocity. When the weight of expected distance in the model is larger, the Tau effect is stronger. The constant velocity model defines the algebraic form in which perceived duration (or distance) is influenced by physical values and expected values but cannot explain why perceived duration (distance) is a weighted average of physical duration (distance) and expected duration (distance), nor can it determine the specific weight values.

Combining the constant velocity assumption with the Bayesian inference perspective, Chen et al. (2016) proposed the constant velocity Bayesian model. In the study, participants needed to reproduce the perceived duration through key press duration, and the psychological process was divided into three stages: (1) Measurement: Physical duration ts enters the nervous system through sensory input to become the psychological measurement duration, i.e., the likelihood. The likelihood follows a normal distribution with mean ts and variance. (2) Estimation: For sequentially presented visual stimuli, individuals have an expectation that they are moving at constant velocity v0. Given movement distance l, the expected duration is . The prior follows a normal distribution with mean and variance $\sigma\tau$. According to Bayes' rule, duration likelihood and prior are integrated to obtain the posterior. (3) Reproduction: In the response phase, the posterior' s optimal estimated duration te is reproduced as the produced duration tp through key press. The algebraic expression for the mean of the optimal posterior distribution is 2 + (Chen et al., 2016). After defining $\sigma\tau$ as weight ω, this algebraic expression is equivalent to the algebraic expression of the model constructed by Jones and Huang (1982). The constant velocity Bayesian model uses the principle of Bayesian optimal estimation to explain why perceived duration (posterior) is a weighted average of physical duration (likelihood) and expected duration (prior), and provides a formula for calculating the weight.

Slow Velocity Bayesian Model

The slow velocity Bayesian model is based on the slow velocity assumption, which has received much support in velocity perception research (Freeman et al., 2010; Stocker & Simoncelli, 2006; Weiss et al., 2002). This assumption states that individuals tend to believe that most objects in daily life are stationary or moving at very slow speeds. Based on this tendency, observers develop an expectation of slow velocity, believing that independent stimuli appearing sequentially at different positions in Kappa and Tau effect studies are the same stimulus moving at slow velocity. Goldreich (2007) proposed the slow velocity Bayesian model based on this assumption to quantitatively explain tactile Kappa and Tau effects. Taking the tactile Kappa effect slow velocity Bayesian model as an example, assume that the neural signals D formed by the brain for the spatial positions x of two tactile stimuli on the skin both follow normal distributions (spatial likelihood), with function expressions ( ) (− 1)2 and (, , τ) (+ τ− 2)2, where x1 and x2 are the positions of the first and second tactile stimuli, σs is the standard deviation representing spatial information uncertainty, and v and τ are the velocity and duration of the "movement" between the two stimulus positions. Similarly, the neural signals D formed by the brain for the time points t of the two tactile stimuli also follow normal distributions (temporal likelihood), with function expressions ( ) 2 and (, τ) (+τ−)2, where the time point of the first tactile stimulus is defined as 0, ts is the time point of the second tactile stimulus, and σt is the standard deviation representing temporal information uncertainty. The two tactile stimuli create an illusion of a stimulus continuously moving on the skin. The probability distribution of the combined neural signals (spatiotemporal joint likelihood) during "movement" is the product of the spatial likelihood distribution and the temporal likelihood distribution, i.e., (, , , τ) (− 1)2+(+ τ− 2)2 2+(+τ−)2. At the same time, observers have an expectation that tactile stimuli "move" to different skin positions at slow velocity. The velocity follows a normal distribution with mean 0 and standard deviation σ (prior), with function expression (, , , τ) 2. Goldreich and colleagues thus proposed the tactile Kappa effect slow velocity Bayesian model, which integrates the slow velocity prior distribution with the spatiotemporal joint likelihood distribution. According to Bayes' rule, they derived the posterior distribution function expression (, , , τ) (− 1)2+(+ τ− 2)2 2+(+τ−)2, used to calculate the magnitude of estimated time (Goldreich, 2007; Goldreich & Tong, 2013).

Logarithmic Constant Velocity Bayesian Model

Both the constant velocity Bayesian model and the slow velocity Bayesian model have limitations. Chen et al. (2016) used these two models to fit participants' behavioral data. Both could adequately predict the trend that participants' perceived time increased with distance. Using AIC values (Akaike information criterion) to assess model fit (Akaike, 1974), the results showed that the slow velocity model, which simultaneously considered temporal and spatial information uncertainty, had better data-fitting ability. The data fitting results also showed that the constant velocity calculated by the constant velocity Bayesian model was approximately 0.2°/s. Previous studies found that older adults' absolute velocity threshold is about 0.12°/s, while young adults' is about 0.09°/s (Snowden & Kavanagh, 2006). The constant velocity is close to the absolute velocity threshold values, indicating that constant velocity is actually slow velocity (Chen et al., 2016). However, the function expression of the slow velocity model is too complex, and the spatial information uncertainty in the model is inferred from previous studies, making it difficult to apply universally to different participants and experimental conditions. In contrast, the constant velocity model has a concise and understandable function expression. Although its data-fitting ability is not as good as the slow velocity model, if the data-fitting degree of the constant velocity model can be improved, it will become a more promising model.

Recently, Chen et al. (2021) proposed the logarithmic constant velocity Bayesian model by incorporating the Weber-Fechner law. The constant velocity (Chen et al., 2016) and slow velocity (Goldreich, 2007; Goldreich & Tong, 2013) Bayesian models mentioned earlier both use linear relationships to establish likelihood functions representing temporal or spatial psychological magnitudes. In psychophysics, the Weber-Fechner law states that physical magnitudes are transformed into psychological magnitudes in a logarithmic form after being registered by the sensory system (Petzschner et al., 2015). This logarithmic transformation relationship has been confirmed in many studies, including distance reproduction (Lakshminarasimhan et al., 2018), duration estimation (de Jong et al., 2021), and number processing (Dehaene et al., 2008). Chen et al. (2016) found that when participants estimated the duration formed by sequentially flashing small circles, the strength of distance' s effect on duration perception (Kappa effect strength) showed a trend of slowing growth as distance increased. Subsequently, Chen et al. (2021) proposed the logarithmic constant velocity Bayesian model based on the original constant velocity Bayesian model (Chen et al., 2016), assuming that physical duration ts and expected duration follow the Weber-Fechner law for psychological representation in logarithmic form. The resulting psychological measurement duration Sm (likelihood) and psychological expected duration Sτ (prior) both follow lognormal distributions. The likelihood function expression is ( ) = $\sqrt{2\pi\sigma}$ (−)2, with mean = ln (1 + and standard deviation σsm. The prior function expression is (Sτ) = $\sqrt{2\pi\sigma}$ τ (τ− 0)2, with mean 0 = ln (1 + and standard deviation σsτ. According to Bayes' rule, the algebraic expression for the mean of the optimal posterior distribution is = 2 + 2 + 2 + 2 0 (Chen et al., 2021). Model fit to participants' behavioral data was assessed using AIC values, and the results showed that the logarithmic constant velocity Bayesian model had better fitting ability than the original constant velocity Bayesian model and could predict the slowing growth trend of the Kappa effect as the distance between small circles increased.

Other Bayesian Models

Proponents of ATOM have proposed Bayesian models to explain spatiotemporal interference effects based on the original theory. ATOM (Walsh, 2003) 主张 that after temporal and spatial information enters the brain, it is transformed into "psychological magnitudes" with the same metric through a unified magnitude system and processed in the parietal lobe (Bueti & Walsh, 2009). Subsequently, researchers (Lambrechts et al., 2013; Martin et al., 2017) integrated ATOM into the Bayesian inference framework. They assumed that estimating the magnitude of a target dimension (time, space, number, etc.) would be influenced by the magnitude of other non-target dimensions, manifested as increasing (decreasing) the magnitude of non-target dimensions increasing (decreasing) the magnitude estimate of the target dimension. Individuals integrate prior assumptions with sensory input information (likelihood) according to Bayes' rule to form the perceived magnitude of the target dimension (posterior). However, researchers have only proposed theoretical constructs for Bayesian models based on ATOM without forming specific function expressions, requiring further research to verify the models' explanatory power.

Some researchers have proposed a dimensional covariation Bayesian model to explain spatiotemporal interference effects. Cai et al. (2018) assumed that time and space dimensions each have independent prior distributions and likelihood distributions. In the priors of both dimensions, there is a covariation relationship between time and space magnitude, meaning that the larger the value of one dimension, the more individuals tend to believe the value of the other dimension is also larger (e.g., going to a farther distance requires more time). Cai et al. (2018) integrated temporal and spatial distribution information to form the dimensional covariation Bayesian model. According to Bayes' rule, they derived the function expression for the posterior distribution mean as = + + , where x=(x1, x2) represents the noisy signals formed by temporal and spatial information in working memory (likelihood), following a multivariate normal distribution with mean vector =(1, 2) and covariance matrix = [2 2]; t represents the prior distribution of temporal and spatial information. To simplify the model, it is assumed to follow a multivariate normal distribution with mean vector (0, 0) and covariance matrix = [1]. However, the researchers did not fit the model to participants' behavioral data, and the model's explanatory power has not received data-level support.

Bayesian Explanation of Spatiotemporal Interference Effects

Researchers have constructed Bayesian models based on different assumptions to explain the mechanisms underlying spatiotemporal interference effects. In the most basic Bayesian model, the posterior distribution mean is a weighted average of the likelihood distribution mean and the prior distribution mean (Körding & Wolpert, 2006). The algebraic expressions for their weights are $\sigma\tau$ and σ , respectively. When the variance of the likelihood distribution is larger than the variance of the prior distribution, the posterior distribution mean will depend more on the prior distribution mean (Petzschner et al., 2015). Bayesian models have been used in tactile and visual spatiotemporal interference effect research. Table 1 provides a detailed introduction to the forms of spatiotemporal information, the three elements of Bayesian models (prior, likelihood, posterior), and explanations of spatiotemporal interference effects in these studies. In the prior assumptions of various Bayesian models, time and space are linked through slow velocity (Goldreich, 2007; Goldreich & Tong, 2013), constant velocity (Chen et al., 2021; Chen et al., 2016), or certain covariation relationships (Cai et al., 2018; Lambrechts et al., 2013; Martin et al., 2017), showing that longer (shorter) distances correspond to longer (shorter) durations. When the uncertainty of the psychological magnitude representation of duration or distance from sensory input is greater—meaning the neural signal noise is larger (the likelihood distribution has greater variability)—individuals will rely more on knowledge and experience (prior assumptions) to make optimal estimates (posterior inference) of duration or distance, causing perceived duration or distance to be disturbed by information from the other dimension in the prior, producing spatiotemporal interference effects.

The Bayesian model perspective holds that the strength of bidirectional interference in spatiotemporal interference effects is not fixed. In past spatiotemporal interference research, if the saliency of temporal stimuli is reduced by decreasing the differences between levels of temporal stimuli (Homma & Ashida, 2015), or if temporal perceptual acuity is reduced by changing the sensory modality of stimulus presentation (for example, temporal perceptual acuity is lower in the visual channel than in the auditory channel) (Cai & Connell, 2015; Loeffler et al., 2018), the neural signal noise of temporal information entering the brain through sensory input increases, and individuals will rely more on spatial information in the prior for decision-making, making the interference effect of spatial information on temporal perception stronger. Similarly, if spatial stimulus saliency is reduced by decreasing the differences between levels of spatial stimuli (Homma & Ashida, 2019), or if spatial perceptual acuity is reduced by changing the sensory modality of stimulus presentation (Cai & Connell, 2015; Loeffler et al., 2018) or skin location (Goldreich, 2007; Goldreich & Tong, 2013), the neural signal noise of spatial information entering the brain through sensory input increases, and individuals will rely more on temporal information in the prior for decision-making, making the interference effect of temporal information on spatial perception stronger. Additionally, Cai et al. (2018) proposed, after constructing the dimensional covariation Bayesian model, that the (a)symmetry of spatiotemporal interference effects is influenced by the relative noise magnitude of temporal and spatial information in working memory (i.e., the relative variance magnitude of the likelihood distributions of time and space). If the two are comparable, symmetric interference between time and space is exhibited; if they differ, the dimension with smaller memory noise (smaller likelihood distribution variance) produces stronger asymmetric interference on the other dimension (Cai & Wang, 2022). Therefore, spatiotemporal interference effects are not necessarily symmetric or asymmetric; their symmetry is influenced by experimental factors such as stimulus saliency and perceptual acuity of time and space. In summary, past research has simultaneously found phenomena where spatial interference on time is greater, temporal interference on space is comparable or even greater, and time and space interfere with each other to equal degrees. The Bayesian model perspective can provide a relatively complete explanation for these phenomena.

Summary and Outlook

Metaphor Theory, A Theory of Magnitude, and Bayesian models are not mutually exclusive but rather explain spatiotemporal interference effects from different perspectives. Metaphor Theory, from the perspective of language use, suggests that people' s habit of using space to metaphorically express time extends to the perceptual domain, causing asymmetric spatial interference on time (Boroditsky, 2000). ATOM, from the perspective of neural mechanisms, 主张 that temporal and spatial information is processed in a common magnitude system in the parietal cortex, producing bidirectional interference effects (Walsh, 2003). Bayesian models, from the perspective of model prediction of behavior, argue that human perceptual processes conform to Bayesian inference principles, where sensory input information (likelihood) has uncertainty, and combining it with experiential information (prior) enables optimal decision-making (posterior). Consequently, perception of information in one dimension is disturbed by information from the other dimension in the prior (Chen et al., 2021; Goldreich, 2007). Additionally, the three theories share common assumptions about the relationship between time and space. Metaphor Theory assumes that longer (shorter) spatial distances lead individuals to believe the corresponding temporal durations are also longer (shorter) (Casasanto & Boroditsky, 2008). ATOM assumes that there is a monotonic mapping relationship between various magnitudes in daily life ("more A-more B" mapping), where an increase (decrease) in one dimension' s magnitude corresponds to an increase (decrease) in another dimension' s magnitude (Bueti & Walsh, 2009). Bayesian models of spatiotemporal perception assume that longer (shorter) distances require longer (shorter) times to traverse in the prior (Cai et al., 2018; Martin et al., 2017; Petzschner et al., 2015). All three theories agree that there is a certain corresponding relationship between the magnitudes of perceived time and space, suggesting that reasonable viewpoints on spatiotemporal relationships from ATOM and Metaphor Theory can be incorporated into the prior assumptions of Bayesian models. By improving prior assumptions, clarifying their neural basis, and constructing more reasonable models in the future, three issues require attention for Bayesian model research in the spatiotemporal interference domain.

First, the explanatory scope of Bayesian models for spatiotemporal interference effects needs expansion. ATOM has been validated at the neural mechanism level (Bueti & Walsh, 2009), but the Bayesian models proposed based on ATOM (Lambrechts et al., 2013; Martin et al., 2017) only describe theoretical constructs without specific function expressions. The dimensional covariation Bayesian model (Cai et al., 2018) does not limit the specific forms of temporal and spatial information, giving the model a more comprehensive explanatory scope, but it has not undergone data-level verification. In contrast, Bayesian models based on constant velocity (Chen et al., 2021; Chen et al., 2016) and slow velocity (Goldreich, 2007; Goldreich & Tong, 2013) assumptions have explicit function expressions and can adequately fit participants' behavioral data, obtaining data-level support and thus having broader application prospects. However, in existing research, constant velocity and slow velocity Bayesian models are still limited to explaining Kappa and Tau effects, where spatial and temporal information are spatial intervals and temporal intervals formed by sequentially presented stimuli. Both models assume that observers will a priori believe that stimuli move to different spatial positions at constant velocity or slow velocity (close to zero velocity), with the product of velocity and "movement time" being "movement distance." In broader spatiotemporal interference effect research, spatial and temporal information can be line length and presentation duration (Magnani et al., 2014; Merritt et al., 2010; Starr & Brannon, 2016), disk or square area and presentation duration (Rammsayer & Verner, 2014, 2015), etc. These experimental stimuli change in spatial magnitude but not in spatial position, making it difficult to directly apply constant velocity or slow velocity Bayesian models for explanation. One possible solution is to assume, based on the dimensional covariation model (Cai et al., 2018) and ATOM (Bueti & Walsh, 2009; Lambrechts et al., 2013), that the magnitudes of time and space have a covariation or monotonic mapping relationship, meaning that longer durations correspond to greater increases in spatial magnitudes such as line length, disk area, or square area. According to this idea, Bayesian models originally limited to explaining Kappa and Tau effects may, by replacing the velocity assumption in the model' s prior with a certain spatiotemporal covariation coefficient, be used to explain a broader range of spatiotemporal interference effects in the future.

Second, the neural mechanisms of spatiotemporal interference based on Bayesian inference need to be clarified. In past Bayesian model research in the spatiotemporal interference domain, researchers have obtained evidence for model explanatory power at the data level through data fitting, but still lack support at the neural mechanism level. In recent years, brain imaging technology has been applied to research on the neural mechanisms of Bayesian inference. On the one hand, researchers have found separate brain representations for prior and likelihood in spatial perception studies. Vilares et al. (2012) used fMRI technology to record participants' brain activation states when judging spatial position and found that likelihood representation was related to activity in early visual motion pathways, while prior representation was related to activity in higher cognitive regions, including the putamen, amygdala, insula, and orbitofrontal cortex. Extending to spatiotemporal interference effect research, future studies should combine various neuroscience techniques to explore the neural representations of prior and likelihood distributions for temporal and spatial information and the neural network basis of their Bayesian integration process. On the other hand, researchers believe that the P3 component of EEG is closely related to Bayesian inference (Kolossa et al., 2015; Kopp et al., 2016). A recent Kappa effect study using EEG technology found that the P2 and P3b components originating from the parietal cortex were related to Bayesian integration where spatial information modulates temporal perception (Cui et al., 2022). Future research can use neural indicators related to Bayesian integration of spatiotemporal interference (such as parietal P2 and P3b components) to further verify the basic assumptions of Bayesian models at the neural mechanism level, such as the constant velocity assumption (Chen et al., 2021; Chen et al., 2016) and the slow velocity assumption (Goldreich, 2007; Goldreich & Tong, 2013).

Third, methods for regulating spatiotemporal interference deserve further exploration. The Bayesian inference perspective holds that if the uncertainty of the likelihood distribution of temporal or spatial information changes, the degree to which individuals rely on information from the other dimension in the prior knowledge during decision-making will also change, thereby showing changes in the strength of spatiotemporal interference. Existing research has found that reducing stimulus saliency by decreasing the differences between levels of temporal or spatial stimuli (Homma & Ashida, 2015, 2019), or reducing perceptual acuity by changing the sensory modality of temporal or spatial stimulus presentation (Cai & Connell, 2015; Loeffler et al., 2018), increases the uncertainty of sensory input temporal or spatial information (likelihood), making it more susceptible to interference from information from the other dimension in the prior. Based on Bayesian theory, future research can regulate spatiotemporal interference from two perspectives. On the one hand, the uncertainty of spatiotemporal information likelihood can be manipulated, for example, by using perceptual training for time and space (Healy et al., 2015), changing stimulus clarity (Schroeger et al., 2021), or signal-to-noise ratio (Petzschner et al., 2015) to enhance or reduce the strength of spatiotemporal interference. On the other hand, attempts can be made to change participants' prior knowledge, for example, by using priming training to reverse the covariation relationship between time and space in participants' experience, linking long distances with short durations, thereby changing the direction of spatiotemporal interference. Effective regulation of spatiotemporal interference effects could have applications in fields with high demands for spatiotemporal perceptual precision, such as automobile driving and aerospace, potentially reducing related accidents.

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