Cognition 273 (2026) 106534

Contents lists available at ScienceDirect

Cognition

journal homepage: www.elsevier.com/locate/cognit

The differential contribution of implicit and explicit priors during motion extrapolation

Giuseppe Di Dona [a,b], Sara Stottmeier [a,b], Alessia Santoni [a,b], Klara Hemmerich [a,b], Luca Ronconi [a,b,*]

[a] Department of Psychology and Cognitive Science, University of Trento, 38068 Rovereto, Italy
[b] School of Psychology, Vita-Salute San Raffaele University, 20132 Milan, Italy

ARTICLE INFO

Keywords:
Visual perception
Visual motion
Motion extrapolation
Prediction
Implicit
Explicit

ABSTRACT

Accurately perceiving the position of moving objects is a fundamental prerequisite for interacting with the environment effectively. However, the brain is inherently "late" in doing so. By the time it encodes the position of a moving object, the object has already moved. To compensate, the brain exploits motion extrapolation, inferring the present position of an object from its past trajectory. Motion extrapolation arises from complex predictive processes, which combine sensory information with implicit and explicit priors to correctly estimate objects' positions. However, how implicit and explicit priors influence motion extrapolation remains unclear. The present studies aimed at understanding their differential contribution using a representational momentum paradigm combined with implicit and explicit priors about objects' motion speed, which in turn heavily impact motion extrapolation. Results showed a clear functional dissociation: while implicit priors resulted in adaptation to motion speed, explicit priors led to the reweighting of perceptual cues. These findings suggest that the representational format of prior information determines which subprocess of motion extrapolation is affected: while implicit priors apparently impact perception itself, explicit priors predominantly impact decision making.

1. Introduction

Accurately perceiving visual motion is necessary to effectively interact with the environment. However, the brain is inherently "late" with respect to the ground truth of objects' motion, as visual perception requires from tens to hundreds of milliseconds (Inui & Kakigi, 2006; Schmolesky et al., 1998). In other words, by the time the brain has built a representation of an object's position, the object will have moved. To perceive and act accurately in the visual world, the brain employs motion extrapolation (Hogendoorn, 2020), a basic mechanism through which an object's present position can be computed based on its past trajectory (but also see (Hubbard, 2010). Motion extrapolation occurs at different levels of neuronal complexity, being hard-wired in the structure of retinal ganglion cells and neurons in the primary visual cortex, but also emerging from high-level predictive processes implemented by a widely interconnected brain network (Turner, Sexton, & Hogendoorn, 2024). Considering predictive extrapolation processes, according to the Bayesian Brain framework, the brain is constantly building internal generative models of the environment, which are used to generate predictions about sensory input based on prior information (Griffiths & Tenenbaum, 2013; Kording, 2014; Moreno-Bote, Knill, & Pouget, 2011). Within a complex interareal network connected via feed-forward and feedback routes, predictions are constantly compared with sensory input, leading to the computation of the prediction error (Friston, 2010); this valuable information is then used to dynamically update and tune the internal models (Bottemanne, 2025; De Ridder, Vanneste, & Freeman, 2014).

The brain exploits different kinds of available prior information that could reduce the prediction error. For instance, when driving in heavy rain, drivers will certainly perceive less traction between the tyres and the road. They might adapt their driving style automatically using this implicit cue, but they could also follow explicit indications on road signs suggesting to reduce driving speed to avoid collisions.

Different studies in the visuomotor domain showed that while the brain is rigid in using implicit priors that automatically drive adaptation (Van Es & Knapen, 2019; Zhou, Kruse, Brower, North, & Joiner, 2022; Zoeller, Lezkan, Paulun, Fleming, & Drewing, 2019), it is more flexible in using explicit priors which cannot induce adaptation (Hutter &

* Corresponding author at: Department of Psychology and Cognitive Science, University of Trento, Corso Bettini 84, 38068 Rovereto, (TN), Italy.
E-mail address: luca.ronconi@unitn.it (L. Ronconi).

https://doi.org/10.1016/j.cognition.2026.106534
Received 22 September 2025; Received in revised form 23 March 2026; Accepted 25 March 2026
Available online 3 April 2026

Taylor, 2018; Jahani, Schwey, Bernier, & Malfait, 2020; Van Es & Knapen, 2019; Zhou et al., 2022; Zoeller et al., 2019) but still promote the volitional use of decision making strategies (Bond & Taylor, 2015). For instance, participants performing a motor task employing experimentally-induced motor perturbations show automatic motor adaptation with high sensitivity to motor errors when they are unaware of such perturbations but as soon as they are explicitly told, they start using volitional strategies with a lower degree of sensitivity to motor errors (Hutter & Taylor, 2018; Jahani et al., 2020; Van Es & Knapen, 2019; Zhou et al., 2022; Zoeller et al., 2019).

Moreover, the mechanisms feeding on implicit and explicit priors are implemented by different neuroanatomical structures (Butcher et al., 2017; Loonis, Brincat, Antzoulatos, & Miller, 2017; Westerberg, Miller, Reber, Cohen, & Paller, 2011), further corroborating their functional specificity in the brain. In particular, while the activity of parietal, occipital cortices (Westerberg et al., 2011) and the cerebellum (Butcher et al., 2017) is associated with implicit adaptation or learning, the activity of frontal, motor and temporal areas is more involved during the implementation of explicit strategies (Jahani et al., 2020; Westerberg et al., 2011). Both can induce performance improvements (Arthur et al., 2023; Campagnoli, Domini, & Taylor, 2021; Gredin, Bishop, Broadbent, Tucker, & Williams, 2018; Poulter, Jackson, Wann, & Berry, 2005), but as a consequence of their neural differentiation, implicit and explicit priors can sometimes compete in perceptual decision making (Alamia, Solopchuk, & Zénon, 2018), thus hampering performance (Mazzoni & Krakauer, 2006).

In the perceptual domain, the precise effect that implicit and explicit information have on visual and motion perception is still unclear. Thakur, Basso, Ditterich, and Knowlton (2021) showed that, in an orientation discrimination task, participants could implicitly learn the statistical distribution of the orientation of the stimuli while also implicitly keeping track of additional regularities of specific stimulus features, irrespective of their awareness. However, despite showing optimised evidence accumulation over time, participants who spontaneously became aware of the regularities still showed the same response bias but had lower accuracy, suggesting that in some cases explicit priors can worsen performance by outweighing sensory information. Other studies showed that explicit probabilistic cues can effectively induce a response bias in visual detection (Tarasi, Di Pellegrino, & Romei, 2022; Tarasi, Martelli, Bortoletto, Di Pellegrino, & Romei, 2023), but the differential influence of implicit and explicit priors remains untested. Another important unanswered question pertains to the "target" of implicit and explicit priors. In particular, studies on prior exploitation in the perceptual domain (Tarasi et al., 2022, 2023; Thakur et al., 2021) successfully employed implicit or explicit priors to induce a response bias by providing cues indicating the probability of the presence (vs. absence) of the stimulus or specific stimulus features. In this way, decision making can be successfully influenced by providing "base-rates", but without necessarily interacting with perceptual processes per se, as observers may merely show a response bias resulting from the application of a strategy.

Therefore, we aimed at directly influencing motion perception by providing implicit or explicit cues to induce beliefs about the moving stimulus features, which in turn modulate motion perception without inducing a mere response bias. Predictive aspects of perception, and particularly those probed by visual motion, have been studied by exploiting the representational momentum (RM) (Hudson, Nicholson, Ellis, & Bach, 2016; Kimura, 2018, 2021; Pascucci & Plomp, 2021; Plunkett & Morales, 2025; Rao et al., 2004; Schmiedchen, Freigang, Rübsamen, & Richter, 2013a; Zucchini, Borzelli, & Casile, 2023), which refers to the phenomenon where a moving object that suddenly stops is often perceived as having slightly continued moving along its trajectory. The seminal study of the classic RM paradigm (Freyd & Finke, 1984) presented a sequence of static images of a bar ("inducer") which was incrementally tilted clockwise at each presentation to induce motion perception (i.e., implied motion). The final "probe" bar could match the orientation of the last inducer, be slightly tilted in the direction of motion, or tilted in the opposite way. When the probe bar was tilted ~1°-2° towards motion's direction, participants judged it as having the same orientation of the last "inducer" more often with respect to when the "inducer" and the "probe" were physically identical (0° tilt) or when the "probe" was tilted in the opposite direction.

Multiple theoretical accounts framed the RM as a window into predictive processes concerning future positions of moving objects generated from high-level cognitive processes (Finke & Shyi, 1988; Freyd & Finke, 1985; Hubbard, 2015; Kerzel, 2002a; White, 2018), giving a functional relevance to the phenomenon supporting perception and action in the visual world. However, it is very important to consider that no consensus has been reached as numerous other theoretical frameworks suggest that the RM arises from one or multiple lower-level visual (Kerzel, 2000, 2002b), perceptual (Bertamini, 2002) or oculomotor biases (Kerzel, Jordan, & Müsseler, 2001). Additionally, others higher-level theories link the RM to mental internalization of physical world's principles (Freyd, 1987; Freyd & Finke, 1984; Hubbard, 1999) or their implicit knowledge (Finke & Shyi, 1988; Kozhevnikov & Hegarty, 2001). Therefore, while interpreting the RM as a reflex of predictive processes provides a functional justification converging with processing needs of the brain, the possibility that such phenomenon represents simpler biases remains open.

Comprehensive accounts of dynamic information processing include the RM in a continuum of localisation biases for moving stimuli (Jancke & Erlhagen, 2010; Merz, Soballa, Spence, & Frings, 2022; Müsseler, Stork, & Kerzel, 2002). In particular, while the RM is an "offset propulsion" effect in which the last position of a moving object is shifted along the direction of motion, "offset repulsion" effects (Merz, Deller, Meyerhoff, Spence, & Frings, 2019; Munger & Owens, 2004; Müsseler et al., 2002) were also reported. The same applies to motion onset as "onset propulsion" or Fröhlich effect (Fröhlich, 1924; Kerzel, 2010; Müsseler & Tiggelbeck, 2013) and "onset repulsion" effects (Hubbard & Motes, 2002; Kirschfeld & Kammer, 1999; Thornton, 2002). According to the "speed prior account" (Merz et al., 2022), these phenomena inherently depend upon speed perception and spatial transformations: as sensory input from moving objects is inevitably characterised by noise and uncertainty, the perceived location of moving stimuli is determined by the combination of such uncertainty with prior information about motion speed. In this Bayesian-like perspective, when actual and expected speed differ, spatial localisation and estimation biases occur. Specifically, if the actual speed is lower than the prior speed expectation, a forward shift in the offset (i.e., representational momentum) and a backward shift in the onset (i.e., Fröhlich effect) are expected, resulting in an expansion of the perceived motion path. Instead, if the actual speed is higher than the expected one, the opposite phenomena occur, resulting in a contraction of the perceived motion space.

While this perspective is not directly suggesting that the RM reflects an extrapolation process, it highlights the pervasiveness of the brain's predictive and corrective capabilities, as sensory evidence is not passively taken but rather combined with prior information and exploited to construct perception. From this point of view it is natural to ask how such priors are formed and whether they can be influenced by newly learned information. In this regard, the RM paradigm offers the possibility of studying the influence of implicit and explicit priors during motion perception as it can be modulated by both, but only when priors are informative about specific perceptual features. For instance, its magnitude can be diminished by providing implicit cues about the position in which the moving object is going to vanish (Hubbard, Kumar, & Carp, 2009). On the contrary, providing prior information targeting the "base rates", corresponding to the actual or the expected probability of a "same" response (i.e., proportion of trials in which the moving bar reappears exactly in the same position), only affects sensitivity and the general response bias but not the magnitude of the final spatial displacement (Hubbard & Lange, 2010). As it would be naturally expected, the RM robustly grows larger in function of motion speed (Freyd

& Finke, 1985). Therefore, with the speed prior account in mind, beliefs about objects' motion speed would serve as an ideal target for the modulation of perceptual processes induced by implicit and explicit priors.

With the present 3 studies we aimed at replicating the effect of rotation speed on RM using a smooth motion paradigm and evaluating the roles of implicit and explicit priors in visual motion extrapolation. In Exp.1, we aimed at replicating the effect of rotation speed on RM by using the smooth-motion version of the classical paradigm (Hubbard & Bharucha, 1988; Schmiedchen, Freigang, Rübsamen, & Richter, 2013b) with a continuously rotating bar at 3 different speeds, and we predicted that the magnitude of the RM would grow in function of rotational speed. In Exp.2, we aimed at elucidating whether implicitly learned priors can influence the effect of speed on motion extrapolation via the RM. To this end, we employed the same paradigm of Exp.1, but while in Exp.1 bars were always grey, in Exp.2 the bars' colors were used as implicit cues to rotational speed in a first 'learning' phase. In a subsequent 'testing' phase, colors became not informative as the rotational speed was held constant. In Exp. 2 participants were not informed about the color-speed mapping, neither in the learning nor in the testing phase. We predicted that if participants implicitly learned the color-speed association during learning, they would use the newly acquired implicit priors to perceive motion. That is, based on findings from the visuomotor domain (Hutter & Taylor, 2018; Jahani et al., 2020; Van Es & Knapen, 2019; Zhou et al., 2022; Zoeller et al., 2019), we expect selective adaptation to occur during the learning phase, assessed by an "inversion" of the effect of speed on the RM: a colored bar moving at high speed during learning but at a slower speed during testing, will show a smaller RM effect, whereas the opposite applies for a colored bar moving slowly during learning but faster during testing.

To further investigate the differential impact of explicit and implicit priors targeting perceptual processes, in Exp.3 we tested whether explicitly learned priors could influence the effect of speed on the RM. This experiment was identical to Exp.2 but this time participants were informed about the color-speed mapping and were reminded of this association before and after each experimental block. In this case, if participants showed adaptation to speed, this would suggest that explicit and implicit priors targeting object features would equally influence low-level automatic processes. In contrast, if explicit information induced the development of a response strategy by only tapping into decision making processes, we would expect participants to show the same modulation of speed both at learning and at testing. However, if a strategy is developed, it is also possible that its exploitation may be dropped during testing if participants realise that the learned rule is not informative anymore.

2. Experiment 1

2.1. Methods

60 healthy adults (34 F, Age = 21.2 ± 3) with normal/corrected-to-normal vision and no history of psychological or neurological disorders were enrolled in the study. All of them signed the informed consent prior to participating. Exp.1, 2 & 3 were carried out in concordance with the ethical standards of the Declaration of Helsinki and approved by the Ethical Committee of the San Raffaele Hospital, Milan and University of Trento. The required sample size was computed via a Power Analysis, performed in GPower (Erdfelder, Faul, & Buchner, 1996) for the main effect of speed. The effect size for the main effect of interest (i.e., Speed) was set to f = 0.25, with $\alpha = 0.05$ and a desired power $(1 - \beta)$ of 0.95. The analysis indicated a minimum of 43 participants to detect the effect. The final sample size was set to $N = 60$ to ensure higher data quality. The same sample size was used also for Exp 2 & 3 to ensure the computation of the main effect of speed, as in Exp.1 and to compare results across experiments. The data collected for Exp.1 were reported in a previous publication focussing on different aspects of this study (Stottmeier et al., 2026). All the other hypotheses and results are novel and not previously explored.

In the RM task, a white fixation dot appeared at the centre of the screen for 750 ± 250 ms (jittered), presented against a dark grey background. Next, the "inducer" bar (length = 8 deg.; width = 1.34 deg., light grey), appeared at the centre of the screen and rotated clockwise at three possible speeds (30, 50, or 70°/s) for 1000 ms before disappearing. After a blank of 250 ms, the "probe" bar was presented for 1000 ms and could appear either in the same orientation of the inducer bar before its disappearance (0° offset), or slightly tilted clockwise or counterclockwise (offsets: ±1°, ±2°, ±3°, ±4°, ±5°). Participants were instructed to report if the probe had the same or different orientation with respect to the final position of the inducer using the "M" and "Z" keys on the keyboard (see Fig. 1A). Response mapping was counterbalanced across participants. Participants performed 20 practice trials before starting the experimental task which was composed of 6 blocks of 165 trials each (990 in total, ≃60 min) with small breaks in between blocks. The experiment was run on a 1920 × 1080 pixel monitor (54.5 × 30 cm) with a 240 Hz refresh rate, using PsychToolbox (Kleiner et al., 2007) for MATLAB (The MathWorks Inc, 2021).

The magnitude of the RM effect was operationalised by computing the weighted mean (WM) (Freyd & Finke, 1985; Hayes & Freyd, 2002), which is a summary measure to represent the shift of the whole response curve. First, the proportion of "same" responses for each of the eleven offsets was calculated. Next, the proportions were multiplied by their associated offset. Then, the obtained scores were summed-up across offsets and finally divided by the sum of the proportions across offsets. This procedure was performed in each individual participant separately by speed. The effect of speed was analysed by a RM-ANOVA in R (R Core Team, 2013), in which speed was imputed as a within-subject factor (levels: 30, 50, 70°/s). In case of violations of sphericity, statistics were corrected by Greenhouse-Geisser. Post-hoc *t*-tests were performed where appropriate, and corrected by False-Discovery Rate (FDR) (Benjamini & Hochberg, 1995).

2.2. Results

The RM-ANOVA showed a main effect of speed, $F(1.81, 107.32) = 7.24$, $p = .001$, $\eta_p^2 = 0.109$. Post-hoc analyses showed a larger RM effect when comparing 30°/s (M = 0.16 ± 0.54) with 50°/s (M = 0.23 ± 0.61) $t(59) = 2.24$, $p_{FDR} = 0.042$, $d = 0.29$, and 70°/s (M = 0.28 ± 0.62), $t(59) = 3.32$, $p_{FDR} = 0.004$, $d = 0.42$. Results are depicted in Fig. 2.

2.3. Discussion

Results of Exp.1 showed a successful replication of the effect of speed on the RM (Freyd & Finke, 1985) where its magnitude grew in function of rotational speed with a smooth rotational motion paradigm. This confirms previous findings on the effect of speed on the representational momentum (Freyd & Finke, 1985) and extends them for the smooth rotational motion paradigm (Hubbard & Bharucha, 1988; Schmiedchen et al., 2013b), corroborating the susceptibility of motion extrapolation to speed in an ecological setting where motion is not simply implied but continuous.

3. Experiment 2

3.1. Methods

60 healthy adults (34 F, Age = 22.6 ± 3.2) with normal/corrected-to-normal vision and no history of psychological or neurological disorders were enrolled in the study. All of them signed the informed consent prior to participating. The trial structure employed in Exp.2 was formally identical to the one employed in Exp.1. However, in the learning phase (blocks 1–4, 660 trials), the bars were colored (azure, orange, purple) and each color corresponded to a specific speed (30, 50,

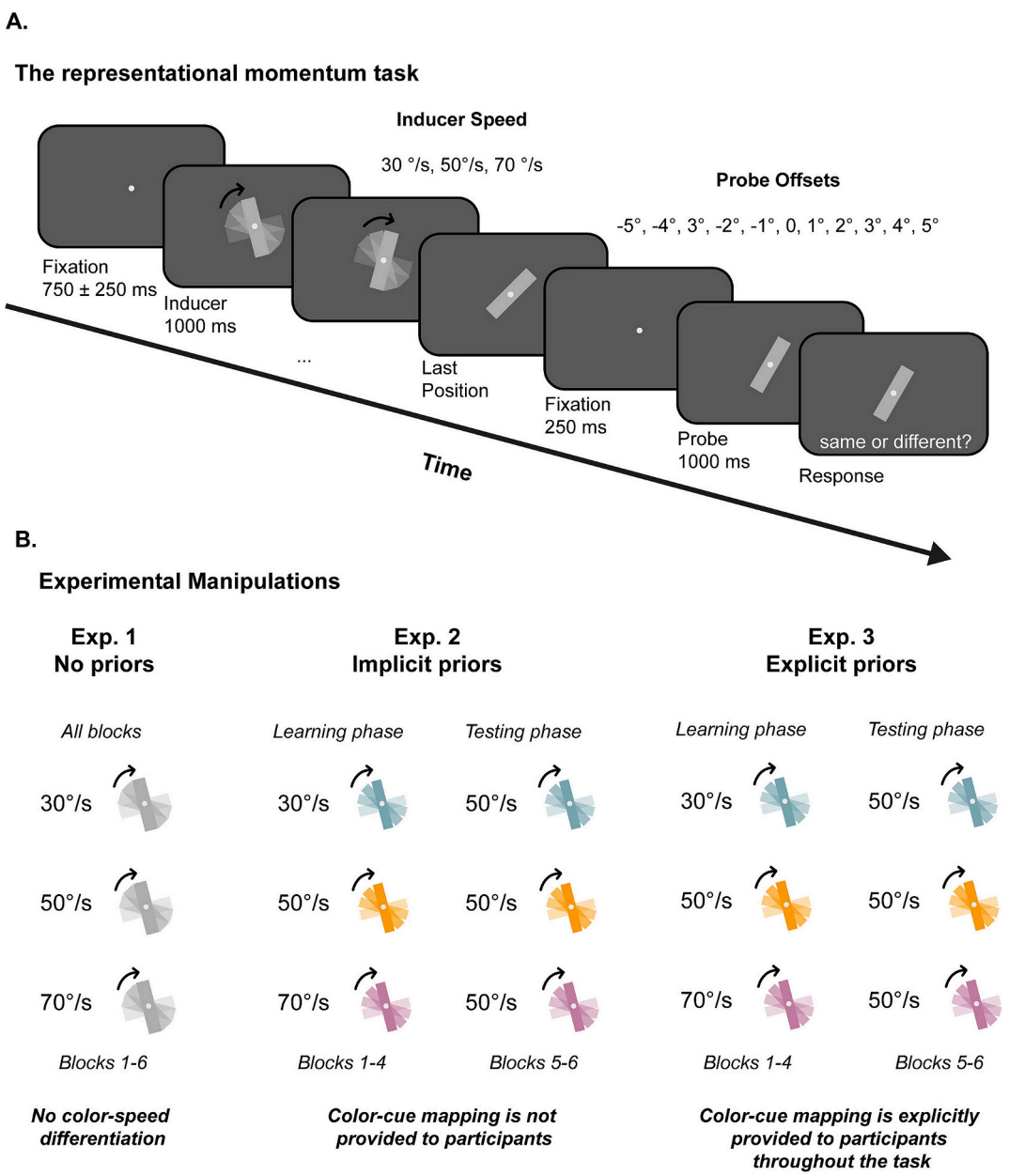


Fig. 1. (A) Schematic illustration of the representational momentum task. (B) Experimental manipulations. In Exp.1 all bars are grey and can equiprobably rotate at 3 different speeds (30, 50, 70°/s). In Exp.2 bars are colored depending on their rotational speed for the first 4 learning blocks, but in the subsequent 2 testing blocks all speeds are set to (50°/s). The color-cue mapping is not provided to the participant. In Exp.3 the task is identical to the one of Exp.2, but participants are informed about the color-speed mapping before the task and at every inter-block pause.

70°/s). In the subsequent testing phase (blocks 5–6, 330 trials) colors were no longer informative about rotation speed, which was fixed at 50°/s for all trials (see Fig. 1B). The speed-color mapping was counterbalanced across participants. At the end of the experiment, participants were administered a questionnaire assessing their awareness of the color-speed mapping.

1) Did you notice anything in particular during the experiment?
2) Did the colors of the bars follow a rule?
   a) If yes, what was the rule?
   b) Did the colors always follow a rule?

Participants were not informed about the meaning of the colors up until debriefing after the experiment.

The WM was computed in each individual participant and separately for all combinations of the factor speed (30, 50, 70°/s) and phase (learning, testing). The differential score (ΔWM) was computed by subtracting the WM of 70°/s from the WM of 30°/s. Data were analysed by means of a two-way RM-ANOVA with speed and learning as within factors. In case of violations of sphericity, statistics were corrected by Greenhouse-Geisser. Post-hoc *t*-tests were performed where appropriate and corrected by FDR.

3.2. Results

Based on the questionnaire, participants remained strikingly naive to the color-speed mapping in the experiment: only 5% ($N = 3$) of them reported to have noticed something particular in the experiment, 36.66% ($N = 22$) reported that color changes followed a rule but only 8% ($N = 5$) reported a possible relationship between color and speed.

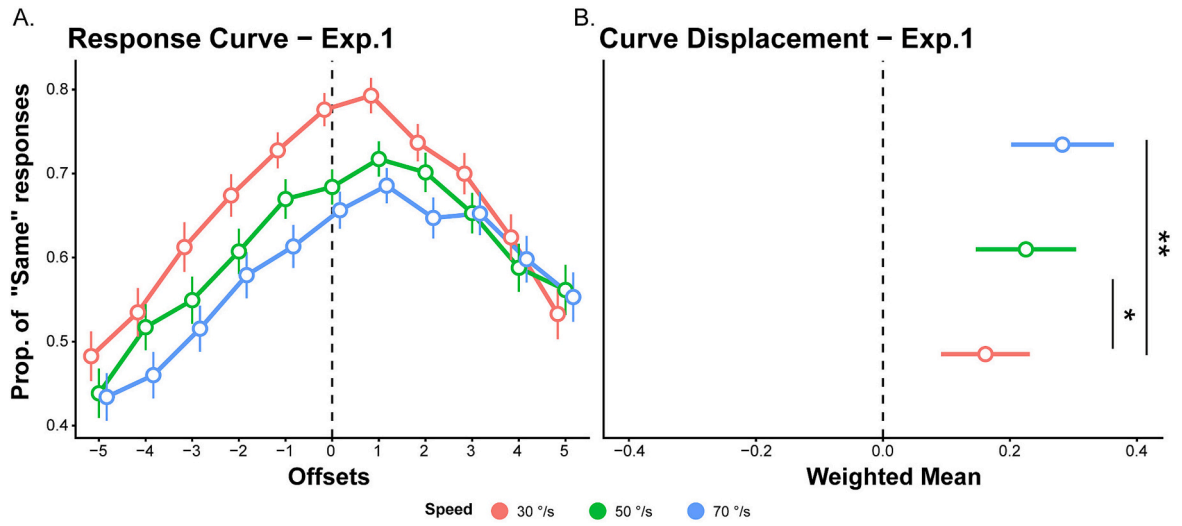


Fig. 2. Results – Exp.1. (A) Dots indicate the proportion of "same" responses (y-axis) for each offset (x-axis) for each speed (red = 30°/s, green = 50°/s, blue = 70°/s). (B) Dots represent the weighted mean (x-axis) for each speed. Error bars indicate the standard error. Asterisks indicate the level of statistical significance of post-hoc tests (* $p_{FDR} < 0.05$, ** $p_{FDR} < 0.01$, ***, $p_{FDR} < 0.001$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Only 5% (N = 3) of participants reported that the rule changed at some point in the experiment. The following analyses were performed by excluding participants who reported that color changes followed a rule (N = 5). The RM-ANOVA showed an interaction effect of speed and phase $F(2, 108) = 6.83$, $p = .002$, $\eta_p^2 = 0.11$. Post-hoc analyses showed a larger WM effect for 70°/s (M = 0.20 ± 0.67) when compared to 30°/s (M = 0.05 ± 0.52) during the learning phase $t(54) = 2.97$, $p_{FDR} = 0.009$, $d = 0.40$ the opposite trend was found in the testing phase, with a larger WM for 30°/s (M = 0.17 ± 0.79) with respect to 70°/s (M = 0.01 ± 0.95) $t(54) = -2.19$, $p_{FDR} = 0.043$, $d = 0.29$. The differential score (ΔWM) computed by subtracting the WM of 70°/s from the WM of 30°/s was also (M = 0.14 ± 0.35) significantly different from the negative one found for the testing phase (M = −0.16 ± 0.54) $t(54) = 3.51$, $p_{FDR} = 0.004$, $d = 0.47$. Results are depicted in Fig. 3.

3.3. Discussion

The results of Exp.2 clearly show that implicit priors influenced the effect of speed on the RM. That is, while the WM grew as a function of the actual rotational speed during the learning phase, the exact opposite pattern emerged in the testing phase, as expected. Specifically, the WM was larger for cues previously associated with slower speed (30°/s) and smaller for cues to higher speed (70°/s), despite the rotational speed being equal across conditions (50°/s). The present result suggests that participants successfully learned the color-speed mapping during learning but combined this knowledge with low-level information (i.e., the actual speed of the inducer bar). As participants learned the color associated with 70°/s, they likely perceived a downward speed shift from the learning to the testing phase (from 70°/s to 50°/s) and over-adjusted their responses, leading to a reduced WM. The same applies to the upward speed shift from 30°/s to 50°/s where the WM increased.

This effect is likely stemming from a combination of learning and selective adaptation to rotational speed. When a test stimulus moves slower (i.e., testing phase) compared to the exposure/adaptation stimulus (i.e., learning phase), the perceived speed will decrease during testing (Gibson, 1937; Goldstein, 1957; Ledgeway & Smith, 1997). The opposite applies when the test stimulus is faster than the exposure one (Hammett, Champion, Morland, & Thompson, 2005; Hietanen, 2015; Hietanen, Crowder, & Ibbotson, 2007; Smith & Edgar, 1991). Our results suggest the presence of selective adaptation processes, based on the learned color-speed mapping. The change in perception of speed at testing, depending on the speed change between learning and testing phases, modulated the effect of speed on the RM in the direction of the speed change. All of those changes in behaviour occurred implicitly as almost all participants were strikingly naive to i) the presence of a relationship between colors and speed and ii) the presence of a change in such a relationship.

The present pattern cannot be ascribed to motion aftereffects (MAE), as they typically last only a few seconds (Culham et al., 1999; Mather, Pavan, Campana, & Casco, 2008; Verstraten, Van Der Smagt, & Van De Grind, 1998). Even if MAE had influenced the results, such effects would have run out after a few trials out of the 330 total trials in the testing phase (~20 min) and would have been canceled out by the remaining ones. This rules out the possibility that the observed effect arises solely from perceptual information, indicating instead that it depends on the combination of implicitly learned priors during the learning phase and perceptual information about rotational speed during the testing phase. This extends previous findings pertaining to the visuomotor domain (Van Es & Knapen, 2019; Zhou et al., 2022; Zoeller et al., 2019) showing that implicit priors lead to adaptation also in the perceptual domain during motion extrapolation.

4. Experiment 3

4.1. Methods

60 healthy adults (34 F, Age = 21.1 ± 1.7) with normal/corrected-to-normal vision and no history of psychological or neurological disorders were enrolled in the study. All of them signed the informed consent prior to participating. The study was carried out in concordance with the ethical standards of the Declaration of Helsinki and approved by the Ethical Committee of the San Raffaele Hospital, Milan and University of Trento. The final sample size was set to $N = 60$ to ensure the computation of the main effect of speed, as in Exp.1 and 2 and to compare results across experiments.

The paradigm of Exp.3 was identical to the one of Exp.2 with the exception that participants were informed about the color-speed relationship before the experiment by the experimenter and by the instructions within the experiment program which were represented right after each pause taken between the blocks. The instructions pertaining to the color speed mapping said: "In the experiment you will be presented with colored rotating bars. Each color corresponds to a specific

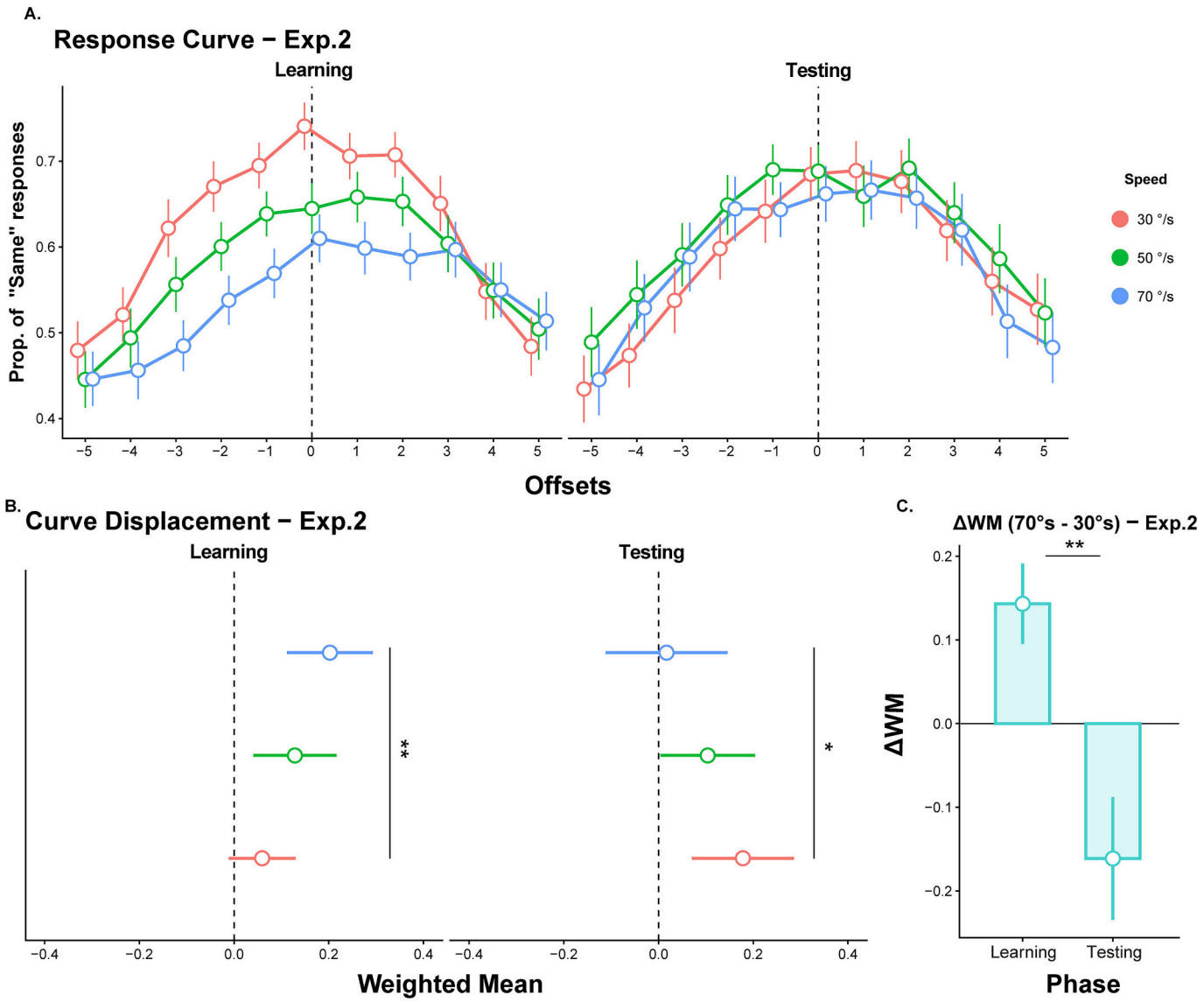


Fig. 3. Results – Exp.2. (A) Dots indicate the proportion of "same" responses (y-axis) at each offset (x-axis) for each speed (red = 30°/s, green = 50°/s, blue = 70°/s), shown separately for the learning phase (blocks 1–4, left plot) and testing phase (blocks 5–6, right plot). (B) Dots represent the weighted mean (x-axis) for each speed for the learning (blocks 1–4, left plot) and testing (blocks 5–6, right plot) phases. (C) Dots represent the differential weighted mean (ΔWM; x-axis), calculated by subtracting the WM obtained at 30°/s from the one obtained at 70°/s for the learning and testing phases (x-axis). Error bars indicate the standard error. Asterisks indicate the level of statistical significance of post-hoc tests (* $p_{FDR} < 0.05$, ** $p_{FDR} < 0.01$, ***, $p_{FDR} < 0.001$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

rotation speed: azure = low speed, orange = medium speed, purple = high speed" (see Fig.1B). The color-speed mapping was counterbalanced across participants. After the experiment, participants were also asked to report which color corresponded to each speed (presented as high, medium or low speed) via a questionnaire.

4.2. Results

81.6% of participants ($N = 49$) correctly reported the color-speed mapping after the experiment. Therefore, the following analyses were performed by discarding the participants that did not correctly report the color speed mapping ($N = 11$). The RM-ANOVA showed an interaction effect of speed and phase $F(1.70, 81.69) = 4.7$, $p = .011$, $\eta_p^2 = 0.09$. Post-hoc analyses showed that during the learning phase a larger WM effect for 70°/s (M = 0.333 ± 0.66) with respect to 30°/s (M = 0.15 ± 0.55) $t(48) = 3.11$, $p_{FDR} = 0.009$, $d = 0.44$, while no differences between learned speeds were found in the testing phase. The differential score computed by subtracting the WM of 70°/s from the WM of 30°/s was also significantly different (M = 0.18 ± 0.40) from the null one found for the testing phase (M = 0.02 ± 0.50) $t(48) = 2.45$, $p_{FDR} = 0.026$, $d = 0.35$. Results are depicted in Fig. 4.

4.3. Discussion

Results from Exp.3 indicated that providing explicit information about speed cues (i.e., color-speed mapping) did not lead to an adaptation to speed in the learning phase. This finding aligns with previous evidence showing that explicit cues cannot induce adaptation in the sensorimotor domain (Hutter & Taylor, 2018; Jahani et al., 2020; Van Es & Knapen, 2019; Zhou et al., 2022; Zoeller et al., 2019). However, the WM was not differentiated by color-speed cues during the testing phase where all speeds were physically equivalent (50°/s). This suggests that participants did not rely on explicit priors during testing, but rather only used perceptual cues to perform the task, despite almost all participants

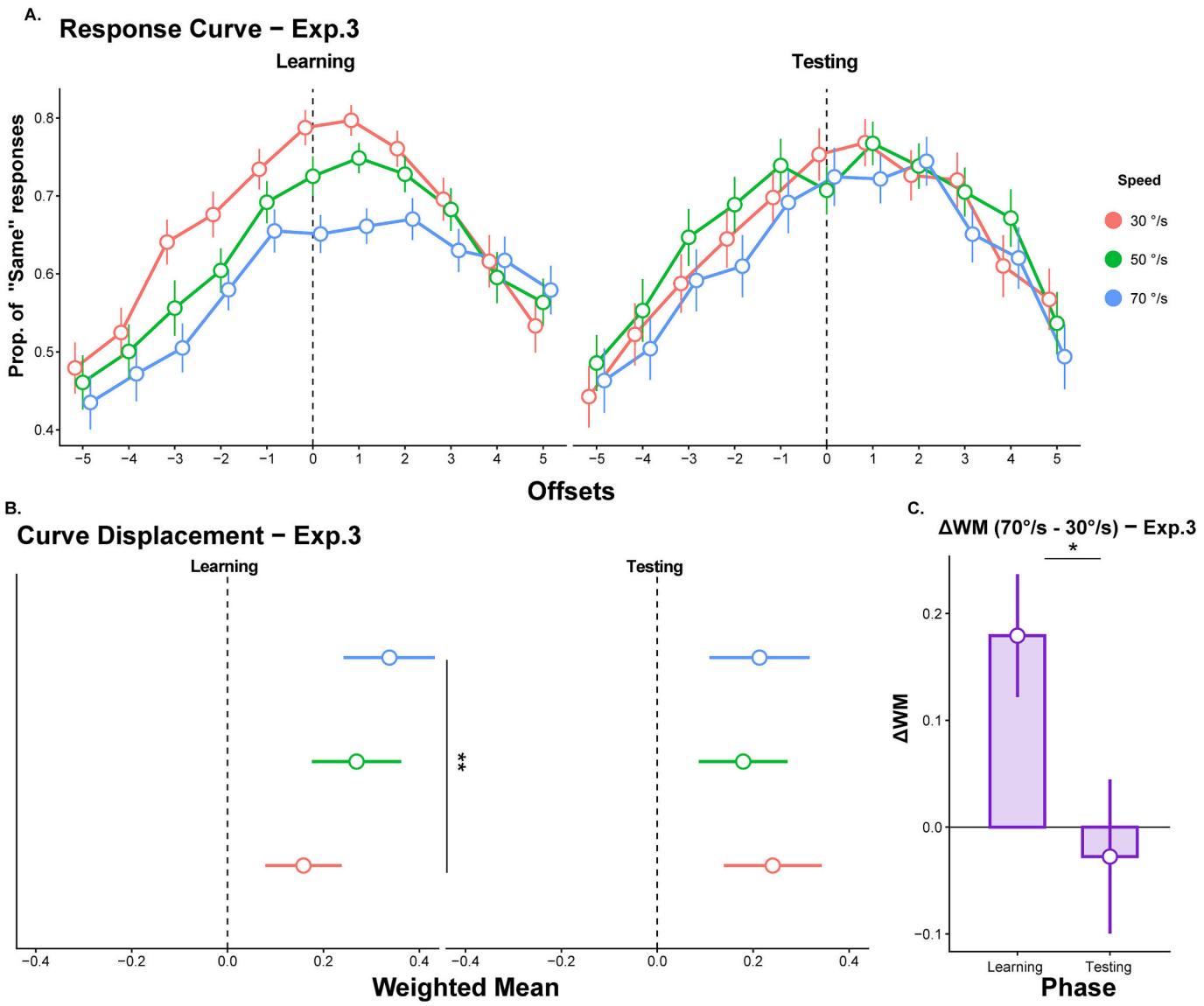


Fig. 4. Results – Exp.3. (A) Dots indicate the proportion of "same" responses (y-axis) for each offset (x-axis) for each speed (red = 30°/s, green = 50°/s, blue = 70°/s) for learning (blocks 1–4, left plot) and testing (blocks 5–6, right plot) phases. (B) Dots represent the weighted mean (x-axis) for each speed for the learning (blocks 1–4, left plot) and testing (blocks 5–6, right plot) phases. (C) Dots represent the differential weighted mean (ΔWM; x-axis) calculated by subtracting the WM obtained at 30°/s from the one obtained at 70°/s for the learning and testing phases (x-axis). Error bars indicate the standard error. Asterisks indicate the level of statistical significance of post-hoc tests (* $p < .05$, ** $p < .01$, ***, $p < .001$). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(81.6%) correctly reported the color-speed mapping in the post-experiment questionnaire. It is possible that the influence of explicit speed priors acquired during the learning phase was overridden by perceptual information in the testing phase, where explicit speed cues conflicted with sensory information. The availability of explicit information might trigger monitoring processes (absent during implicit learning) that constantly evaluate the validity of the rule by comparing perceptual input with rule-based expectations. When the rule is conflicting with perceptual input, it is discarded generating a prediction error. This monitoring process would likely require a stronger involvement of attention. However, contrarily to this expectation, attention is actually thought to enhance adaptation to motion speed (Bartlett, Graf, Hedger, & Adams, 2019; Sunaert, Van Hecke, Marchal, & Orban, 2000). If attention played a role in determining the present pattern, a strong inversion of the WM across 30°/s and 70°/s speed cues would have been observed, as seen in Exp.2. Therefore, the possibility that the present pattern stems from attentional modulation to objects' features is weak. To this regard, the generation of the prediction error is fairly automatic (Friston, 2005) and is dissociated from the error awareness (Dumsky, Maier, Di Gregorio, & Steinhauser, 2025). However, the present results cannot clarify whether such monitoring processes would be determined by conscious processes or not, and how they might impede or mask adaptation processes.

5. Cumulative analyses of temporal dynamics of RM

While representational momentum is a widely studied phenomenon, its temporal dynamics have never been properly addressed. Doing so would possibly better characterise its putative "functional" relevance to predictive and extrapolation processes (Hudson et al., 2016; Kimura, 2018, 2021; Pascucci & Plomp, 2021; Plunkett & Morales, 2025; Rao et al., 2004; Schmiedchen et al., 2013a; Zucchini et al., 2023) which are constantly tuned based on upcoming information to fight uncertainty (Bottemanne, 2025; De Ridder et al., 2014; Friston, 2010), its

permeability to implicit cues (Hubbard et al., 2009) and its sensitivity to expertise (Anderson, Gottwald, & Lawrence, 2019; Blättler, Ferrari, Didierjean, Van Elslande, & Marmèche, 2010). Moreover, it is reasonable to think that the influence of explicit and implicit cues varies over time by triggering adaptation or learning processes (Hutter & Taylor, 2018; Van Es & Knapen, 2019; Zhou et al., 2022), possibly acting on solid priors (Merz et al., 2022).

Therefore, to explore the temporal dynamics of the effect of speed on the RM as well as the different influences of implicit and explicit priors over time, we computed the WM in consecutive subsets of trials along the whole three experiments. The WM was computed from the proportion of "same" responses in windows of 60 trials, sliding across the whole dataset with a step of 10 trials. The width of the sliding window ensured a sufficient amount of trials to compute proportions and the step size granted smoothed estimates across time. This was done separately for each participant, speed (30, 50, 70°/s) and phase (Learning, Testing). For each speed, each unit of observation consisted in the ordered repetition of that speed in the dataset in order to study the modulations of the WM in function of quantity of exposition to a specific speed rather than its unspecific modulations over time. This means that while each data point refers to an observation recorded later in time with respect to the previous data point, the two data points are not necessarily immediately subsequent at the trial level (e.g., data point 1 may correspond to trial 7 while data point 2 may correspond to trial 10). We obtained WM estimates for each participant and speed at 23 windows. Next, the ΔWM was computed by subtracting the WM obtained at 30°/s from the one obtained at 70°/s in each window. This index refers to the direction and magnitude of the effect of real rotational speed in Exp.1, while in Exp.2 and Exp.3 is used to probe the effects of adaptation and response strategies across learning and testing phases. The ΔWM was analysed via linear mixed effects model with the 'lmerTest' package (Kuznetsova, Brockhoff, & Christensen, 2017) in R. The model included a third-degree raw polynomial expansion of the "window" continuous predictor to capture potentially nonlinear trends over time. The 3rd-degree polynomial expansion resulted in a model with the lowest AIC when compared to a simple linear predictor or a 2nd-degree polynomial. Fixed effects included the main effects of polynomial-transformed Window (linear, quadratic, and cubic terms) and Experiment (levels: 1, 2, 3), as well as their interaction. The participant was included as a random intercept. Among the 23 windows, windows from 1 to 16 only include trials in the learning phase, while trials from windows 17 to 23 only include trials from the testing phase. Note that in Exp.1 labeling windows as pertaining to learning, transition and testing phases is meaningless, but the data represents a "baseline" for Exp.2 and 3. Model results were analysed via Chi-square tests (type III) and post-hoc tests (FDR-corrected) were computed via 'emmeans' package (Lenth, Singmann, Love, Buerkner, & Herve, 2018) in R. Observed power was computed for the interaction between Window and Experiment via simulation using the 'simr' package (Green & MacLeod, 2016) in R and showed that with $N = 164$ the observed power was 0.99 [0.98.56 0.99.72]. Lastly, an explorative autocorrelation analysis was run on the moving ΔWM separately within each experiment by computing correlations between the ΔWM at each window and each of the remaining windows. Outlier participants were removed from this analysis when their ΔWM surpassed ±3SD in more than 3 windows ($N = 4$). *P*-values were FDR-corrected for multiple comparisons.

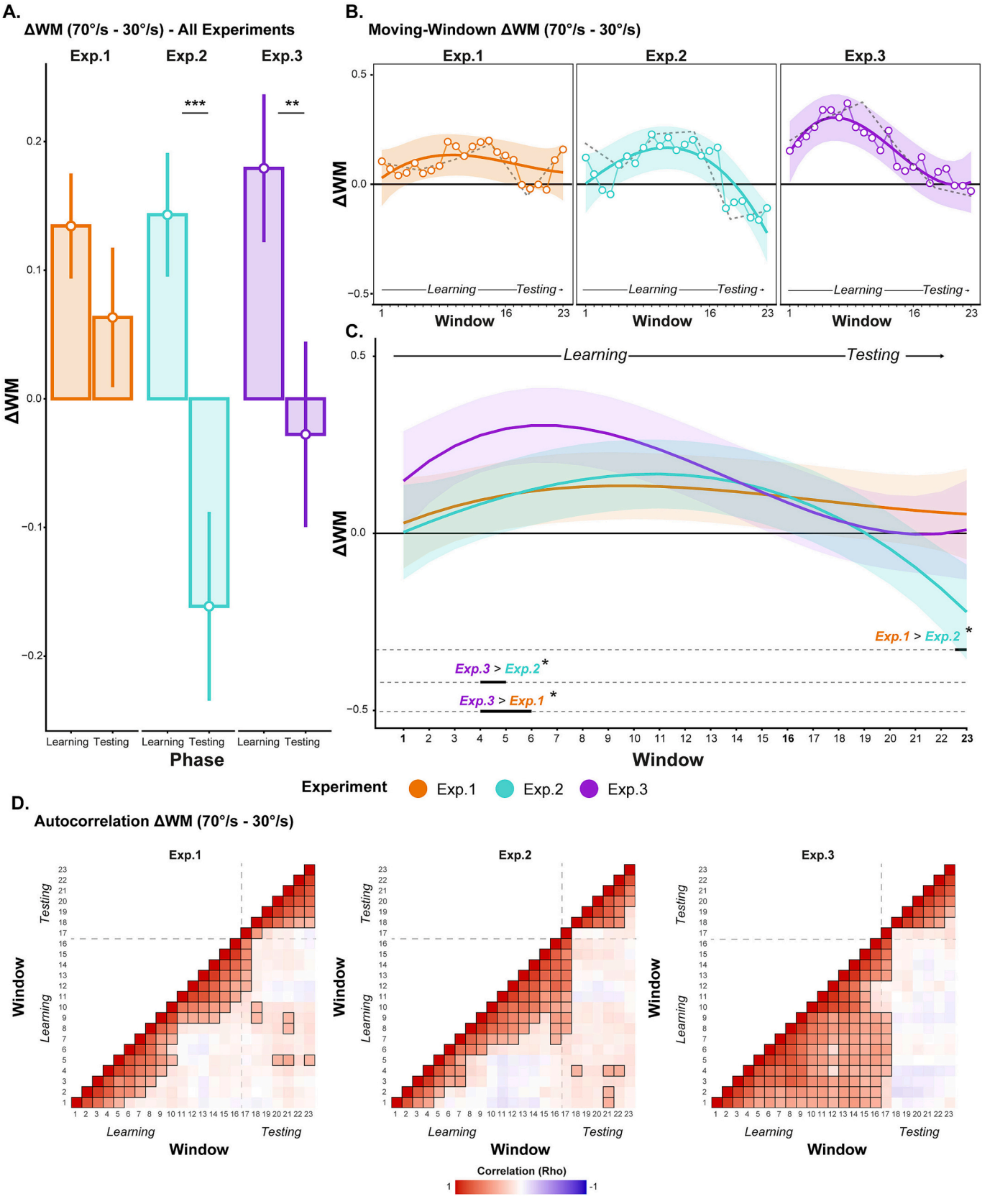
Chi-square tests performed on linear mixed models showed a significant interaction between Window and Experiment $\chi(6) = 31.99$, $p < .001$ and a main effect of Window $\chi(3) = 69.32$, $p < .001$. Model estimates show a growing ΔWM for all experiments during the learning phase, with the effect being most pronounced in Exp.3 (Fig. 5B). Exp.1 shows an oscillatory pattern over time, while Exp.2 shows a pronounced dip where the ΔWM changes sign, clearly indicating the adaptation effect. Exp.3 also shows a dip over time; however, unlike Exp.2, it levels off into a plateau approaching zero. Post-hoc tests were run comparing the WM at each window between each experiment (FDR-corrected). During the learning phase (windows 1–16), the WM in Exp.3 was significantly larger than the one of Exp.1 between the 4th and the 6th window (all $p_{FDR} < 0.05$) but also larger than the one of Exp.2 between the 4th and the 5th (all $p_{FDR} < 0.05$). During the testing phase (windows 17–23), the ΔWM in Exp.2 was significantly more negative with respect to Exp.1 (window 22–23; all $p_{FDR} < 0.05$). Next, we also tested for the presence of linear, cubic and quadratic temporal trends of the ΔWM for each experiment and compared them (See Table 1). Exp.1 showed no significant linear, or cubic trends but only a marginally significant inverted quadratic trend ($M = -0.005 \pm 0.005$, $p = .053$). Exp.2 showed a significant inverted quadratic trend ($M = -0.002 \pm 0.0003$, $p_{FDR} < 0.001$) only. Exp.3 showed a significant negative linear trend ($M = -0.029 \pm 0.006$, $p_{FDR} < 0.001$), a significant inverted quadratic trend ($M = -0.001 \pm 0.0004$, $p_{FDR} = 0.012$) and a significant cubic trend ($M = 0.0001 \pm 0.00007$, $p_{FDR} = 0.021$). When comparing trends across experiments, Exp.3 showed a stronger negative linear trend with respect to Exp.1 ($p_{FDR} = 0.006$) and Exp.2 ($p_{FDR} = 0.006$). Exp 2 also showed a stronger inverse quadratic trend with respect to Exp.1 ($p_{FDR} = 0.012$) and Exp.3 but this time only marginally significant ($p = .052$). Additionally, Exp.3 showed a marginally significant stronger cubic trend with respect to Exp.2 ($p = .025$). These results show a steep linear decrease of ΔWM in Exp.3 as compared to Exp.1 & 2, possibly due to a larger growth of ΔWM in the learning phase. A quadratic decrease of ΔWM over time was found in Exp 2 & 3, reflected by a concave downward curve. The rate of decline of the curve was stronger in Exp.2 compared to Exp.1. A significant cubic trend was found only in Exp. 3, as portrayed by the presence of at least two inflection points (see Fig. 5B, C); this was only marginally stronger than the one of Exp.2. The results of the autocorrelation analysis, depicted in Fig. 5D, show that while Exp.1 and 2 show a comparable temporal autocorrelation profile where every block correlates with the following 4–5 (possibly partially influenced by the overlap in the moving windows), Exp.3 shows a stable and diffused autocorrelation in the learning phase where every block correlates with one another.

6. General discussion

The present study aimed at replicating the effect of speed on the RM during smooth motion and investigating the role of implicit and explicit priors on motion extrapolation, through three experiments. In particular, we evaluated priors' influence on objects' features that consequently impact motion extrapolation without interacting with base-rates.

First, we successfully replicated the effect of speed on the RM. Second, we highlighted the differential influences of implicit and explicit priors on speed perception in the context of motion extrapolation, where implicit priors led to selective adaptation while explicit priors did not. Furthermore, the time-resolved comparison between experiments (Fig. 5C) showed that implicit cues to speed did not influence the magnitude of the speed-induced modulation of RM (ΔWM), when comparing the learning phase of Exp. 2 (implicit cues to speed) with the temporally equivalent phase of Exp. 1 (no cues to speed). In contrast, explicit speed cues (Exp.3) amplified the effect of speed on RM (ΔWM) relative to when implicit cues were present (Exp.2) or absent (Exp.1) in the same period. Instead, during the testing phase, implicit priors (Exp.2) led to the inversion of the ΔWM, with WM becoming larger for cues to slower speed (i.e. 30°/s) and smaller for cues to higher speed (i.e. 70°/s). Differently, when explicit priors were provided (Exp.3), ΔWM approached zero, showing no induced differentiation based on the previous exposition to the color-speed mapping in the learning phase.

This pattern of results confirms that while implicit priors (Exp.2) led to implicit learning and selective adaptation, as portrayed by the inversion of the ΔWM from learning to testing, explicit priors (Exp.3) did not. Instead, receiving explicit information boosted the effect of speed during the learning period as indicated by the larger ΔWM, suggesting that participants indeed used explicit prior information during



(caption on next page)

Fig. 5. Results of the cumulative time-resolved analysis. (A) Bars represent the differential weighted mean (ΔWM; x-axis) calculated by subtracting the WM obtained at 30°/s from the one obtained at 70°/s for the learning and testing phases (x-axis) for all experiments (orange = Exp.1, cyan = Exp.2, purple = Exp.3). Error bars indicate the standard error. (B) Dots represent the ΔWM calculated in the time-resolved analysis for each of the 23 (learning: 1–16; testing: 17–23) windows for all the experiments. Lines represent the mixed model fit with 95% CI. Black dashed lines underneath the colored ones represent data from the original experimental blocks ($N = 6$) (C) Lines represent the model fits of ΔWM calculated in the time-resolved analysis. Black lines below represent the windows in which significant differences were found between the ΔWM of all the experiments. Asterisks indicate the level of statistical significance of post-hoc tests (* $p_{FDR} < 0.05$, ** $p_{FDR} < 0.01$, *** $p_{FDR} < 0.001$). (D) Autocorrelation matrices of the ΔWM of all the experiments. The color in each square represents the strength and direction of the correlation coefficient (Pearson's ρ; red = positive, blue = negative) of the correlations of the ΔWM performed between all the couples of windows. Black borders and low opacity indicate statistically significant correlations ($p < .05$). Dashed grey lines indicate the boundaries of each phase (learning, transition, testing). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Post-hoc tests of polynomial trends of the liner mixed model on the ΔWM and contrasts.

	Experiment			Contrast		
Trend type	*Exp.1*	*Exp.2*	*Exp.3*	*Exp.1* vs *2*	*Exp.1* vs *3*	*Exp.2* vs *3*
Linear	−0.004 ± 0.0054 $p_{FDR} = 0.73$	−0.005 ± 0.005 pFDR = 0.43	−0.029 ± 0.006 pFDR <0.001***	z = 0.11 pFDR = 0.90	z = 3.03 pFDR = 0.006**	z = 2.85 pFDR = 0.006**
Quadratic	−0.0007 ± 0.0003 pFDR = 0.053	−0.002 ± 0.0003 pFDR <0.001***	−0.001 ± 0.0004 pFDR = 0.012*	z = 2.87 pFDR = 0.012*	z = 0.64 pFDR = 0.52	z = −2.112 pFDR = 0.52
Cubic	0.00004 ± 0.00006 pFDR = 0.53	0.00004 ± 0.00006 pFDR = 0.53	0.0001 ± 0.00007 pFDR = 0.021*	z = 0.93 pFDR = 0.35	z = −1.51 pFDR = 0.19	z = −2.37 pFDR = 0.053

the learning phase. Still, as soon as the explicit information deviated from the ground truth during the testing phase, low-level perceptual information possibly outweighed explicit priors, as shown by ΔWM approaching zero (Fig. 5B,C). The autocorrelation analysis clearly showed that while there is relatively similar autocorrelation in Exp.1 and 2, in which ΔWM in every window is correlated with values from few previous windows as it would be expected considering the smoothing approach employed, in Exp.3 there is a stable autocorrelation within all windows in the learning phase which abruptly stops between the transition and the testing phase (Fig. 5D). The stability of the autocorrelation structure, which is absent in Exp.1 & 2, suggests that providing explicit cues to speed induced the persistence of an internal state characterised by an interaction between perceptual cues and explicit priors. The enlargement of the ΔWM during learning might likely stem from the correspondence between a rule acquired via explicit priors and perceptual input, establishing a context where the rule is valid. As soon as the rule mismatched from perceptual input in the testing phase, ΔWM abruptly approached zero and the autocorrelation suddenly disappeared. This suggests that the rule was simply dropped and participants relied more on low-level perceptual cues to speed (i.e., the actual rotation speed which was always 50°/s) to perform the task.

Therefore, providing explicit priors likely modulated the weight of perceptual input depending on context. When explicit priors match perceptual input, they may optimize perceptual decision making by lowering the weight of perceptual information and reducing computation costs and this would reasonably explain why an effect of selective learning and adaptation was not found as in Exp.3. Instead, when explicit priors do not match with perceptual input, perceptual cues regain the weight in the decision making process. Therefore, even if explicit priors "targeted" object features that later influence motion extrapolation and not directly base-rates (Tarasi et al., 2022, 2023; Thakur et al., 2021), they still likely influenced the decision making process more rather than perception itself.

Overall, the present studies show that implicit and explicit priors pertaining motion speed – a pivotal information to perform motion extrapolation – act at different levels of perceptual decision making. In particular, only implicit priors appear to influence perceptual processes by inducing adaptation, whereas explicit information seems to affect more decision making by reweighting perceptual input, in line with results from the visuomotor domain (Hutter & Taylor, 2018; Jahani et al., 2020; Van Es & Knapen, 2019; Zhou et al., 2022; Zoeller et al., 2019). This nicely aligns with the notion that implicit and explicit priors act via different mechanisms (Bond & Taylor, 2015; Thakur et al., 2021), even when priors pertain to stimulus features rather than base rates directly.

Importantly, results provided some patterns which can be explained by the speed prior account (Merz et al., 2022). In Exp. 2, it is reasonable to think that providing implicit color cues to rotation speed during the learning phase resulted in a shift of the speed prior – that would be the "default" expectation about moving objects' speed – towards the actual speed of moving objects. While the difference is not statistically significant, the higher WM (across speeds) observed in Exp 1 (M = 0.22 ± 0.05) and 2 (M = 0.13 ± 0.05) during the learning phase, might suggest that the propulsion of the offset is reduced in magnitude as a result of the shift of speed priors towards the real speeds in Exp.2. In Exp. 3, where explicit cues to speed did not alter the averaged WM much (M = 0.25 ± 0.05) with respect to Exp.1, the growth in the ΔWM during the learning phase (Fig. 5C) might still have been fostered by a shift of the prior speeds towards the actual speed. Nonetheless, data pertaining to perceived position of motion onset and offset, which would be necessary to study the continuum of spatial biases properly (Merz et al., 2022), were not recorded in the present work. Future studies should consider acquiring this data to investigate effects of prior manipulation, possibly at the individual level.

Few interesting questions remain open. First, it is unclear whether the results of Exp.3 stem from the interaction between implicit and explicit priors or from explicit priors alone. In other words, do explicit priors impede adaptation altogether, or is there a competition between implicit and explicit priors during motion extrapolation? Adaptation to motion speed is thought to be a fairly automatic process occurring within motion sensitive neural areas such as V5/MT+ (Burton, McKeefry, Barrett, Vakrou, & Morland, 2009; Lingnau, Ashida, Wall, & Smith, 2009) along the dorsal visual stream, which is the primary pathway for motion processing (Livingstone & Hubel, 1988; Morrone et al., 2000). In addition, neural responses related to the perception of speed changes occur after ~200–300 ms from stimulus presentation (Amano, Nishida, & Takeda, 2006, p. 200). The fact that adaptation to motion speed occurs in secondary visual areas, also receiving projections from frontal and pre-frontal regions (Di Dona & Ronconi, 2023), and that speed-induced modulations emerge relatively late in time, suggests the possibility for their modulability, operated by top-down processes fed by explicit information (Schendan, Searl, Melrose, & Stern, 2003). Therefore, while results highlighted the differences concerning motion extrapolation induced by implicit and explicit priors, we cannot conclude that providing explicit priors impeded the formation and exploitation of implicit priors in Exp.3.

Another important aspect pertains to the temporal dynamics of the influence of implicit and explicit priors. Results showed that implicit priors lead to selective learning and adaptation (i.e., ΔWM reversal in Exp.2), while explicit priors did not (i.e., ΔWM approached zero in Exp.3). However, we cannot exclude that explicit priors could have led to a ΔWM reversal if given additional time. While this issue clearly applies to any study investigating temporal dynamics of psychological processes, future studies could use longer testing phases to better investigate the temporal unfolding of these processes.

A last important metacognitive aspect, which remained untested in the present study, pertains to the confidence of participants while performing perceptual decisions. A recent study showed that while both implicit and explicit base-rates priors can bias perceptual decision making, only explicit priors boost confidence ratings (Schorn & Knowlton, 2025). Further studies should consider acquiring this information as it would provide an index of the weight given to explicit priors, trial by trial.

In conclusion, the present work shows that implicit and explicit priors targeting perceptual processes shape motion extrapolation by inducing adaptation or strategy use, respectively. Therefore, the priors' locus of action (i.e., perception or decision-making) appears to be determined by their informational format (i.e., implicit or explicit) rather than by their intended target, irrespective of whether such priors are informative about perceptual features of moving objects or base-rates.

CRediT authorship contribution statement

Giuseppe Di Dona: Visualization, Software, Methodology, Formal analysis, Conceptualization, Writing – review & editing, Writing – original draft. **Sara Stottmeier:** Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Alessia Santoni:** Investigation, Data curation, Writing – review & editing. **Klara Hemmerich:** Visualization, Formal analysis, Writing – review & editing. **Luca Ronconi:** Supervision, Resources, Project administration, Funding acquisition, Conceptualization, Writing – review & editing.

Funding statement

L.R. and G.D.D. were supported by funding from the Italian Ministry of University and Research (Bando PRIN 2022; grant number 2022H4ZRSN to L.R). L.R. and K.H. were supported by funding from the Italian Ministry of University and Research (Bando PRIN PNRR 2022; grant number P2022XAKXL to L.R.).

Declaration of competing interest

None.

Acknowledgments

The present work was performed by Sara Stottmeier in fulfillment of the requirements for obtaining the PhD degree at Vita-Salute San Raffaele University, Milano, Italy. We thank Anna Rosini, Martina Ceresi, Simona Cerreta, Giorgia Bucci & Martina Dal Maso for their help in data collection.

Data availability

All the data generated during the experiment described in this article is available on Open Science Framework, at the following link: https://osf.io/gwyc6/overview

References

Alamia, A., Solopchuk, O., & Zénon, A. (2018). Strong conscious cues suppress preferential gaze allocation to unconscious cues. *Frontiers in Human Neuroscience, 12*. https://doi.org/10.3389/fnhum.2018.00427

Amano, K., Nishida, S., & Takeda, T. (2006). MEG responses correlated with the visual perception of velocity change. *Vision Research, 46*(3), 336–345. https://doi.org/10.1016/j.visres.2005.04.017

Anderson, D. N., Gottwald, V. M., & Lawrence, G. P. (2019). Representational momentum in the expertise context: Support for the theory of event coding as an explanation for action anticipation. *Frontiers in Psychology, 10*, 1838. https://doi.org/10.3389/fpsyg.2019.01838

Arthur, T., Brosnan, M., Harris, D., Buckingham, G., Wilson, M., Williams, G., & Vine, S. (2023). Investigating how explicit contextual cues affect predictive sensorimotor control in autistic adults. *Journal of Autism and Developmental Disorders, 53*(11), 4368–4381. https://doi.org/10.1007/s10803-022-05718-5

Bartlett, L. K., Graf, E. W., Hedger, N., & Adams, W. J. (2019). Motion adaptation and attention: A critical review and meta-analysis. *Neuroscience & Biobehavioral Reviews, 96*, 290–301. https://doi.org/10.1016/j.neubiorev.2018.10.010

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B: Methodological, 57*(1), 289–300.

Bertamini, M. (2002). Representational momentum, internalized dynamics, and perceptual adaptation. *Visual Cognition, 9*(1–2), 195–216.

Blättler, C., Ferrari, V., Didierjean, A., Van Elslande, P., & Marmèche, E. (2010). Can expertise modulate representational momentum? *Visual Cognition, 18*(9), 1253–1273. https://doi.org/10.1080/13506281003737119

Bond, K. M., & Taylor, J. A. (2015). Flexible explicit but rigid implicit learning in a visuomotor adaptation task. *Journal of Neurophysiology, 113*(10), 3836–3849. https://doi.org/10.1152/jn.00009.2015

Bottemanne, H. (2025). Bayesian brain theory: Computational neuroscience of belief. *Neuroscience, 566*, 198–204. https://doi.org/10.1016/j.neuroscience.2024.12.003

Burton, M. P., McKeefry, D. J., Barrett, B. T., Vakrou, C., & Morland, A. B. (2009). Disruptions to human speed perception induced by motion adaptation and transcranial magnetic stimulation. *European Journal of Neuroscience, 30*(10), 1989–1998. https://doi.org/10.1111/j.1460-9568.2009.06993.x

Butcher, P. A., Ivry, R. B., Kuo, S.-H., Rydz, D., Krakauer, J. W., & Taylor, J. A. (2017). The cerebellum does more than sensory prediction error-based learning in sensorimotor adaptation tasks. *Journal of Neurophysiology, 118*(3), 1622–1636. https://doi.org/10.1152/jn.00451.2017

Campagnoli, C., Domini, F., & Taylor, J. A. (2021). Taking aim at the perceptual side of motor learning: Exploring how explicit and implicit learning encode perceptual error information through depth vision. *Journal of Neurophysiology, 126*(2), 413–426. https://doi.org/10.1152/jn.00153.2021

Culham, J. C., Dukelow, S. P., Vilis, T., Hassard, F. A., Gati, J. S., Menon, R. S., & Goodale, M. A. (1999). Recovery of fMRI activation in motion area MT following storage of the motion aftereffect. *Journal of Neurophysiology, 81*(1), 388–393. https://doi.org/10.1152/jn.1999.81.1.388

De Ridder, D., Vanneste, S., & Freeman, W. (2014). The Bayesian brain: Phantom percepts resolve sensory uncertainty. *Neuroscience & Biobehavioral Reviews, 44*, 4–15. https://doi.org/10.1016/j.neubiorev.2012.04.001

Di Dona, G., & Ronconi, L. (2023). Beta oscillations in vision: A (preconscious) neural mechanism for the dorsal visual stream? *Frontiers in Psychology, 14*, Article 1296483. https://doi.org/10.3389/fpsyg.2023.1296483

Dumsky, J., Maier, M. E., Di Gregorio, F., & Steinhauser, M. (2025). Error awareness can occur in the absence of an error-related negativity. *Psychophysiology, 62*(10), Article e70128. https://doi.org/10.1111/psyp.70128

Erdfelder, E., Faul, F., & Buchner, A. (1996). GPOWER: A general power analysis program. *Behavior Research Methods, Instruments, & Computers, 28*, 1–11.

Finke, R. A., & Shyi, G. C. (1988). Mental extrapolation and representational momentum for complex implied motions. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14*(1), 112.

Freyd, J. J. (1987). Dynamic mental representations. *Psychological Review, 94*(4), 427.

Freyd, J. J., & Finke, R. A. (1984). Representational momentum. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 10*(1), 126.

Freyd, J. J., & Finke, R. A. (1985). A velocity effect for representational momentum. *Bulletin of the Psychonomic Society, 23*(6), 443–446.

Friston, K. (2005). A theory of cortical responses. *Philosophical Transactions of the Royal Society, B: Biological Sciences, 360*(1456), 815–836.

Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience, 11*(2), 127–138.

Fröhlich, F. W. (1924). Über die Messung der Empfindungszeit. *Pflügers Archiv für die Gesamte Physiologie des Menschen und der Tiere, 202*(1), 566–572. https://doi.org/10.1007/BF01723521

Gibson, J. J. (1937). Adaptation with negative after-effect. *Psychological Review, 44*(3), 222–244. https://doi.org/10.1037/h0061358

Goldstein, A. G. (1957). Judgments of visual velocity as a function of length of observation time. *Journal of Experimental Psychology, 54*(6), 457–461. https://doi.org/10.1037/h0044965

Gredin, N. V., Bishop, D. T., Broadbent, D. P., Tucker, A., & Williams, A. M. (2018). Experts integrate explicit contextual priors and environmental information to improve anticipation efficiency. *Journal of Experimental Psychology: Applied, 24*(4), 509.

Green, P., & MacLeod, C. J. (2016). SIMR: An R package for power analysis of generalized linear mixed models by simulation. *Methods in Ecology and Evolution, 7*(4), 493–498. https://doi.org/10.1111/2041-210X.12504

Griffiths, T. L., & Tenenbaum, J. B. (2013). *Predicting the future as Bayesian inference: People combine prior knowledge with observations when estimating duration and extent*.
Hammett, S. T., Champion, R. A., Morland, A. B., & Thompson, P. G. (2005). A ratio model of perceived speed in the human visual system. *Proceedings of the Royal Society B: Biological Sciences, 272*(1579), 2351–2356. https://doi.org/10.1098/rspb.2005.3239
Hayes, A. E., & Freyd, J. J. (2002). Representational momentum when attention is divided. *Visual Cognition, 9*(1–2), 8–27. https://doi.org/10.1080/13506280143000296
Hietanen, M. A. (2015). The relative contributions of global and local acceleration components on speed perception and discriminability following adaptation. *Vision Research, 115*, 135–141. https://doi.org/10.1016/j.visres.2015.06.010
Hietanen, M. A., Crowder, N. A., & Ibbotson, M. R. (2007). Contrast gain control is drift-rate dependent: An informational analysis. *Journal of Neurophysiology, 97*(2), 1078–1087. https://doi.org/10.1152/jn.00991.2006
Hogendoorn, H. (2020). Motion extrapolation in visual processing: Lessons from 25 years of flash-lag debate. *The Journal of Neuroscience, 40*(30), 5698–5705. https://doi.org/10.1523/JNEUROSCI.0275-20.2020
Hubbard, T. L. (1999). How consequences of physical principles influence mental representation: The environmental invariants hypothesis. *Proceedings of the Twentieth Annual Conference of the Cognitive Science Society*, 1228–1228.
Hubbard, T. L. (2010). *Approaches to representational momentum: Theories and models. Space and time in perception and action* (pp. 338–365).
Hubbard, T. L. (2015). The varieties of momentum-like experience. *Psychological Bulletin, 141*(6), 1081–1119. https://doi.org/10.1037/bul0000016
Hubbard, T. L., & Bharucha, J. J. (1988). Judged displacement in apparent vertical and horizontal motion. *Perception & Psychophysics, 44*(3), 211–221. https://doi.org/10.3758/BF03206290
Hubbard, T. L., Kumar, A. M., & Carp, C. L. (2009). Effects of spatial cueing on representational momentum. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 35*(3), 666–677. https://doi.org/10.1037/a0014870
Hubbard, T. L., & Lange, M. (2010). Prior probabilities and representational momentum. *Visual Cognition, 18*(7), 1063–1087. https://doi.org/10.1080/13506281003665708
Hubbard, T. L., & Motes, M. A. (2002). Does representational momentum reflect a distortion of the length or the endpoint of a trajectory? *Cognition, 82*(3), B89–B99.
Hudson, M., Nicholson, T., Ellis, R., & Bach, P. (2016). I see what you say: Prior knowledge of other's goals automatically biases the perception of their actions. *Cognition, 146*, 245–250. https://doi.org/10.1016/j.cognition.2015.09.021
Hutter, S. A., & Taylor, J. A. (2018). Relative sensitivity of explicit reaiming and implicit motor adaptation. *Journal of Neurophysiology, 120*(5), 2640–2648. https://doi.org/10.1152/jn.00283.2018
Inui, K., & Kakigi, R. (2006). Temporal analysis of the flow from V1 to the Extrastriate cortex in humans. *Journal of Neurophysiology, 96*(2), 775–784. https://doi.org/10.1152/jn.00103.2006
Jahani, A., Schwey, A., Bernier, P.-M., & Malfait, N. (2020). Spatially distinct Beta-band activities reflect implicit sensorimotor adaptation and explicit re-aiming strategy. *The Journal of Neuroscience, 40*(12), 2498–2509. https://doi.org/10.1523/JNEUROSCI.1862-19.2020
Jancke, D., & Erlhagen, W. (2010). *Bridging the gap: A model of common neural mechanisms underlying the Fröhlich effect, the flash-lag effect, and the representational momentum effect*.
Kerzel, D. (2000). Eye movements and visible persistence explain the mislocalization of the final position of a moving target. *Vision Research, 40*(27), 3703–3715.
Kerzel, D. (2002a). A matter of design: No representational momentum without predictability. *Visual Cognition, 9*(1–2), 66–80. https://doi.org/10.1080/13506280143000322
Kerzel, D. (2002b). Memory for the position of stationary objects: Disentangling foveal bias and memory averaging. *Vision Research, 42*(2), 159–167.
Kerzel, D. (2010). *The Fröhlich effect: Past and present*.
Kerzel, D., Jordan, J. S., & Müsseler, J. (2001). The role of perception in the mislocalization of the final position of a moving target. *Journal of Experimental Psychology: Human Perception and Performance, 27*(4), 829.
Kimura, M. (2018). Visual mismatch negativity and representational momentum: Their possible involvement in the same automatic prediction. *Biological Psychology, 139*, 178–185. https://doi.org/10.1016/j.biopsycho.2018.10.015
Kimura, M. (2021). Prediction, suppression of visual response, and modulation of visual perception: Insights from visual evoked potentials and representational momentum. *Frontiers in Human Neuroscience, 15*, Article 730962. https://doi.org/10.3389/fnhum.2021.730962
Kirschfeld, K., & Kammer, T. (1999). The Fröhlich effect: A consequence of the interaction of visual focal attention and metacontrast. *Vision Research, 39*(22), 3702–3709.
Kleiner, M., Brainard, D., Pelli, D. G., Ingling, A., Murray, R., & Broussard, C. (2007). What's new in Psychtoolbox-3? A free cross-platform toolkit for psychophysics with Matlab & GNU/Octave [Abstract supplement]. In *Proceedings of the Conference on Visual Perception (ECVP), Berlin* (pp. 1–89).
Kording, K. P. (2014). Bayesian statistics: Relevant for the brain? *Current Opinion in Neurobiology, 25*, 130–133. https://doi.org/10.1016/j.conb.2014.01.003
Kozhevnikov, M., & Hegarty, M. (2001). Impetus beliefs as default heuristics: Dissociation between explicit and implicit knowledge about motion. *Psychonomic Bulletin & Review, 8*(3), 439–453.
Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software, 82*(13), 1–26. https://doi.org/10.18637/jss.v082.i13
Ledgeway, T., & Smith, A. T. (1997). Changes in perceived speed following adaptation to first-order and second-order motion. *Vision Research, 37*(2), 215–224. https://doi.org/10.1016/S0042-6989(96)00122-8
Lenth, R., Singmann, H., Love, J., Buerkner, P., & Herve, M. (2018). *Emmeans: Estimated marginal means, aka least-squares means. R package version, 1(1)* (p. 3).
Lingnau, A., Ashida, H., Wall, M. B., & Smith, A. T. (2009). Speed encoding in human visual cortex revealed by fMRI adaptation. *Journal of Vision, 9*(13). https://doi.org/10.1167/9.13.3, 3–3.
Livingstone, M., & Hubel, D. (1988). Segregation of form, color, movement, and depth: Anatomy, physiology, and perception. *Science, 240*(4853), 740–749. https://doi.org/10.1126/science.3283936
Loonis, R. F., Brincat, S. L., Antzoulatos, E. G., & Miller, E. K. (2017). A Meta-analysis suggests different neural correlates for implicit and explicit learning. *Neuron, 96*(2), 521–534.e7. https://doi.org/10.1016/j.neuron.2017.09.032
Mather, G., Pavan, A., Campana, G., & Casco, C. (2008). The motion aftereffect reloaded. *Trends in Cognitive Sciences, 12*(12), 481–487. https://doi.org/10.1016/j.tics.2008.09.002
Mazzoni, P., & Krakauer, J. W. (2006). An implicit plan overrides an explicit strategy during visuomotor adaptation. *The Journal of Neuroscience, 26*(14), 3642–3645. https://doi.org/10.1523/JNEUROSCI.5317-05.2006
Merz, S., Deller, J., Meyerhoff, H. S., Spence, C., & Frings, C. (2019). The contradictory influence of velocity: Representational momentum in the tactile modality. *Journal of Neurophysiology, 121*(6), 2358–2363.
Merz, S., Soballa, P., Spence, C., & Frings, C. (2022). The speed prior account: A new theory to explain multiple phenomena regarding dynamic information. *Journal of Experimental Psychology: General, 151*(10), 2418–2436. https://doi.org/10.1037/xge0001212
Moreno-Bote, R., Knill, D. C., & Pouget, A. (2011). Bayesian sampling in visual perception. *Proceedings of the National Academy of Sciences, 108*(30), 12491–12496. https://doi.org/10.1073/pnas.1101430108
Morrone, M. C., Tosetti, M., Montanaro, D., Fiorentini, A., Cioni, G., & Burr, D. C. (2000). A cortical area that responds specifically to optic flow, revealed by fMRI. *Nature Neuroscience, 3*(12), 1322–1328. https://doi.org/10.1038/81860
Munger, M., & Owens, T. R. (2004). Representational momentum and the flash-lag effect. *Visual Cognition, 11*(1), 81–103.
Müsseler, J., Stork, S., & Kerzel, D. (2002). Comparing mislocalizations with moving stimuli: The Fröhlich effect, the flash-lag, and representational momentum. *Visual Cognition, 9*(1–2), 120–138. https://doi.org/10.1080/13506280143000359
Müsseler, J., & Tiggelbeck, J. (2013). The perceived onset position of a moving target: Effects of trial contexts are evoked by different attentional allocations. *Attention, Perception, & Psychophysics, 75*(2), 349–357.
Pascucci, D., & Plomp, G. (2021). Serial dependence and representational momentum in single-trial perceptual decisions. *Scientific Reports, 11*(1), 9910. https://doi.org/10.1038/s41598-021-89432-9
Plunkett, D., & Morales, J. (2025). Representational momentum transcends motion. *Psychological Science, 36*(12), 930–940. https://doi.org/10.1177/09567976251395074
Poulter, D. R., Jackson, R. C., Wann, J. P., & Berry, D. C. (2005). The effect of learning condition on perceptual anticipation, awareness, and visual search. *Human Movement Science, 24*(3), 345–361. https://doi.org/10.1016/j.humov.2005.06.005
R Core Team. (2013). *R: A language and environment for statistical computing*.
Rao, H., Han, S., Jiang, Y., Xue, Y., Gu, H., Cui, Y., & Gao, D. (2004). Engagement of the prefrontal cortex in representational momentum: An fMRI study. *NeuroImage, 23*(1), 98–103. https://doi.org/10.1016/j.neuroimage.2004.05.016
Schendan, H. E., Searl, M. M., Melrose, R. J., & Stern, C. E. (2003). An fMRI study of the role of the medial temporal lobe in implicit and explicit sequence learning. *Neuron, 37*(6), 1013–1025. https://doi.org/10.1016/S0896-6273(03)00123-5
Schmiedchen, K., Freigang, C., Rübsamen, R., & Richter, N. (2013). A comparison of visual and auditory representational momentum in spatial tasks. *Attention, Perception, & Psychophysics, 75*(7), 1507–1519. https://doi.org/10.3758/s13414-013-0495-0
Schmolesky, M. T., Wang, Y., Hanes, D. P., Thompson, K. G., Leutgeb, S., Schall, J. D., & Leventhal, A. G. (1998). Signal timing across the macaque visual system. *Journal of Neurophysiology, 79*(6), 3272–3278. https://doi.org/10.1152/jn.1998.79.6.3272
Schorn, J. M., & Knowlton, B. J. (2025). Implicitly learned bias impacts decision-making but not metacognition. *Consciousness and Cognition, 131*, Article 103857. https://doi.org/10.1016/j.concog.2025.103857
Smith, A. T., & Edgar, G. K. (1991). The separability of temporal frequency and velocity. *Vision Research, 31*(2), 321–326. https://doi.org/10.1016/0042-6989(91)90121-K
Stottmeier, S., Di Dona, G., Santoni, A., Hemmerich, K., Bertini, C., & Ronconi, L. (2026). Tracking electrophysiological dynamics of prior exploitation in visual motion perception. *Biological Psychology, 205*, Article 109231. https://doi.org/10.1016/j.biopsycho.2026.109231
Sunaert, S., Van Hecke, P., Marchal, G., & Orban, G. A. (2000). Attention to speed of motion, speed discrimination, and task difficulty: An fMRI study. *NeuroImage, 11*(6), 612–623. https://doi.org/10.1006/nimg.2000.0587
Tarasi, L., Di Pellegrino, G., & Romei, V. (2022). Are you an empiricist or a believer? Neural signatures of predictive strategies in humans. *Progress in Neurobiology, 219*, Article 102367. https://doi.org/10.1016/j.pneurobio.2022.102367
Tarasi, L., Martelli, M. E., Bortoletto, M., Di Pellegrino, G., & Romei, V. (2023). Neural signatures of predictive strategies track individuals along the autism-schizophrenia continuum. *Schizophrenia Bulletin, 49*(5), 1294–1304. https://doi.org/10.1093/schbul/sbad105
Thakur, V. N., Basso, M. A., Ditterich, J., & Knowlton, B. J. (2021). Implicit and explicit learning of Bayesian priors differently impacts bias during perceptual decision-

making. *Scientific Reports, 11*(1), 16932. https://doi.org/10.1038/s41598-021-95833-7
The MathWorks Inc. (2021). *MATLAB (Version 9.11) [Software]*. The MathWorks Inc. https://www.mathworks.com.
Thornton, I. (2002). The onset repulsion effect. *Spatial Vision, 15*(2), 219–243. https://doi.org/10.1163/15685680252875183
Turner, W., Sexton, C., & Hogendoorn, H. (2024). Neural mechanisms of visual motion extrapolation. *Neuroscience & Biobehavioral Reviews, 156*, Article 105484. https://doi.org/10.1016/j.neubiorev.2023.105484
Van Es, D. M., & Knapen, T. (2019). Implicit and explicit learning in reactive and voluntary saccade adaptation. *PLoS One, 14*(1), Article e0203248. https://doi.org/10.1371/journal.pone.0203248
Verstraten, F. A., Van Der Smagt, M. J., & Van De Grind, W. A. (1998). Aftereffect of high-speed motion. *Perception, 27*(9), 1055–1066.
Westerberg, C. E., Miller, B. B., Reber, P. J., Cohen, N. J., & Paller, K. A. (2011). Neural correlates of contextual cueing are modulated by explicit learning. *Neuropsychologia, 49*(12), 3439–3447. https://doi.org/10.1016/j.neuropsychologia.2011.08.019
White, P. A. (2018). Is the perceived present a predictive model of the objective present? *Visual Cognition, 26*(8), 624–654. https://doi.org/10.1080/13506285.2018.1530322
Zhou, W., Kruse, E. A., Brower, R., North, R., & Joiner, W. M. (2022). Motion state-dependent motor learning based on explicit visual feedback is quickly recalled, but is less stable than adaptation to physical perturbations. *Journal of Neurophysiology, 128*(4), 854–871. https://doi.org/10.1152/jn.00520.2021
Zoeller, A. C., Lezkan, A., Paulun, V. C., Fleming, R. W., & Drewing, K. (2019). Integration of prior knowledge during haptic exploration depends on information type. *Journal of Vision, 19*(4), 20. https://doi.org/10.1167/19.4.20
Zucchini, E., Borzelli, D., & Casile, A. (2023). Representational momentum of biological motion in full-body, point-light and single-dot displays. *Scientific Reports, 13*(1), 10488. https://doi.org/10.1038/s41598-023-36870-2