#### Do prediction errors of perceived exertion inform the level of running pleasure?

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### **Open Science Framework (OSF) repository link**

The recommended stage 1 and stage 2 registered report protocol can be found in <a href="https://osf.io/y8d9m">https://osf.io/y8d9m</a> (stage 1) and in <a href="https://osf.io/czgmp">https://osf.io/czgmp</a> (stage 2). The Jamovi file containing the data of the pilot study and the main/preregistered study, linear mixed models (LMM) analyses (including model specification for reproducing the LMM analyses using other statistical software), the R codes and outputs of the power simulation are openly available on the OSF website <a href="https://osf.io/2sb86/">https://osf.io/2sb86/</a>.

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# Abstract

Humans have the ability to mentally project themselves into future events (prospective thinking) to promote the implementation of health-oriented behaviors, such as the planning of daily physical exercise sessions. Nevertheless, it is currently unclear whether and how prospective thinking can assist individuals in generating future predictions about their own bodily states, such as when anticipating the level of perceived exertion to be experienced in a forthcoming physical exercise session, and whether these predictions influence the subjective experience of pleasure in a session. Here, based on the literature on reward prediction errors, we argue that running sessions that are experienced with a lower intensity of ratings of perceived exertion (RPE) than expected are associated with a higher level of pleasure, and vice versa. To test this hypothesis, we created a novel marker, the RPE-based prediction error, by comparing RPE before (prospective RPE) and after (retrospective RPE) each running session among participants in a start-to-run program (N = 66). Retrospective ratings of running pleasure was assessed by the participant after each running session of the program. Using this approach, linear mixed models showed that a positive RPE-based prediction error (lower score of retrospective RPE than prospective RPE) is associated with a higher level of retrospective pleasure. This study thus demonstrates that the use of prospective and retrospective RPE is beneficial for predicting the experience of running pleasure. We further discuss how future studies should help to better understand the impact of RPE-based prediction error on exercise pleasure and whether this new marker may be used to ultimately impact humans' commitment to physical exercise.

*Keywords:* physical exercise, prospective thinking, rating of perceived exertion, pleasure, prediction error.

# Introduction

Prospective thinking refers to humans' ability to mentally simulate the future (for a review, see Schacter et al., 2017). It allows individuals to effectively prepare for upcoming events and facilitates the enactment of goal-directed actions and the planning of behaviors, including health behaviors (Brevers et al., 2023; D'Argembeau et al., 2010; Schacter et al., 2017). A core feature of prospective thinking is that it enables one to flexibly retrieve and recombine past information into mental simulations of future events (D'Argembeau et al., 2010; Schacter et al., 2017). These memory-based processes have been extensively studied with experimental tasks that involve the extraction of information about locations, objects, and people, as well as more schematic and conceptual knowledge to envision general goals or events (Schacter et al., 2017). Humans can thus engage in various forms of prospection, including episodic future thinking (e.g., by imagining themselves in a particular place at a specific time, bringing specific details to mind) and semantic future thinking (i.e., thinking about the future in a general, abstract manner; Demblon & D'Argembeau, 2014).

Nevertheless, it is currently unclear how prospective thinking unfolds when making future predictions about one's own bodily states, such as when anticipating the intensity of perceived exertion (i.e., the subjective intensity of effort, strain, discomfort, and/or fatigue that is experienced during physical exercise; Hutchinson, 2020; Robertson and Noble, 1997) of a forthcoming physical exercise session. Indeed, the level of perceived exertion is usually indexed while exercising (i.e., momentary ratings of perceived exertion, [RPE]; e.g., "What intensity of exertion do you feel now?") or directly after the exercise session (i.e., retrospective RPE; e.g., "What intensity of exertion did you feel during this session?"; or "How was your workout?"; Foster et al., 2001; Haile et al., 2015; Robertson & Noble, 1997). These types of measures have provided a fine-grained understanding of how people manage exercise intensity through pacing strategies (i.e., conscious effort management throughout an

exercise bout) to prevent metabolic and biomechanical failures (e.g., fatigue accumulation, slower rates of neuromuscular recovery, overtraining syndrome; e.g., Meeusen et al., 2013; Thiel et al., 2018; Vieira et al., 2022).

A key observation from the literature on RPE is that increased perceived levels of exertion are negatively linked with the intensity of pleasure felt during the session of physical exercise (for a theoretical review, see Ekkekakis et al., 2011; for recent studies, see Hartman et al., 2019; Hutchinson et al., 2020; Frazão et al., 2016). It has also been evidenced that decreasing the intensity of a resistance exercise session can elicit higher levels of experienced and retrospective pleasure toward physical exercise (e.g., Hutchinson et al., 2023). Additionally, positive changes in hedonic responses during moderate intensity exercise have been linked to future physical activity (Rhodes & Kates, 2015). Taken together, these findings suggest that experienced and retrospective levels of pleasure toward physical exercise substantially affect the individual appraisal of the activity and may ultimately impact future engagement and commitment to physical exercise. In other words, physical exercise will be more likely reinforced by sessions that are experienced as pleasant, whereas if it is perceived as unpleasant it will more likely be avoided (e.g., Teixeira et al., 2022).

Here we aim to extend current knowledge about the impact of perceived exertion on the level of pleasure experienced during physical exercise. Specifically, we aim to better identify exercise sessions that lead to an increase (or decrease) in the remembered level of pleasure (i.e., retrospective pleasure) that was experienced by an individual during physical exercise. We argue that prospective thinking can provide a key insight into this research question. In this study, prospective thinking refers to individuals' anticipation of the intensity of a forthcoming session of physical exercise, that is, *before* the physical exercise session has started (e.g., "What intensity of exertion do you expect to feel during this session?"). We labeled this process as *prospective RPE*. As previously mentioned, few studies have

examined prospective or anticipatory types of RPE. Nevertheless, preliminary evidence revealed that mismatches (either overestimation or underestimation) between anticipated and experienced exertion is associated with lower frequency of daily physical activity, negative attitudes about physical exercise, higher body mass index, as well as poor cardiorespiratory fitness (Haile et al., 2008; Hunt et al., 2007; Kane et al., 2010; Poulton et al., 2002). The present study thus aims to push forward in this direction by examining whether mismatches between anticipated and remembered exertion can inform the level of pleasure that was felt by the individual during a physical exercise session. To do so, we capitalize on the main dynamic pertaining to *reward prediction errors* (Schultz et al., 2016; Kieslich et al., 2021).

A key tenet from the literature on reward processing is that the reactivity to reward does not depend on the value of rewarding outcomes per se, but is instead driven by the difference between expected and actual outcomes, namely a reward prediction error. This pattern has been evidenced by studies showing that, when a rewarding outcome is better than expected, it induces more pleasure than a reward that matches prior expectations (i.e., a positive reward prediction error; for a review, see Schultz et al., 2016; Kieslich et al., 2021). Against this background, and given the correspondence between RPE and pleasure, we posited that physical exercise sessions that are experienced with a lower level of perceived exertion than anticipated (i.e., a positive RPE-based prediction error) should be associated with a higher level of subjective pleasure experienced during a session of physical exercise. In other words, experiencing less exertion than expected should induce a higher level of pleasure during physical exercise, and vice versa (i.e., a negative RPE-based prediction error). We tested this hypothesis by using RPE and ratings of running pleasure filled out by participants just before (prospective RPE) and directly after (retrospective RPE, retrospective running pleasure) running sessions as a part of a start-to-run program.

# Method

# **Transparency and Openness**

As a Stage 2 registered report that has been recommended by Peer Community In (PCI) Registered Reports (see Brevers et al., 2024; see also Dienes, 2023, 2024), the present study adheres to the Transparency and Openness Promotion (TOP) Guidelines. The recommended stage 1 and stage 2 registered report protocol can be found in <u>https://osf.io/y8d9m</u> (stage 1) and in <u>https://osf.io/czgmp</u> (stage 2). The Jamovi file containing the data of the pilot study and the main/preregistered study, linear mixed models (LMM) analyses (including model specification for reproducing the LMM analyses using other statistical software), the R codes and outputs of the power simulation are openly available on the Open Science Framework (OSF) website <u>https://osf.io/2sb86/</u>. The design summary table of our Stage 1 registered report can be found in the online supplementary material of this paper.

# **Ethics**

The protocol of the study was approved by the Ethics Committee of Saint-Luc University Hospital (UCLouvain; #2022/21JUI/247).

# **Participants**

Sixty-six participants (all > 18 years) took part in our start-to-run study (23 males, 43 females; age [years]: mean = 20.9, median = 21, SD = 2.10, range = 18-27; height [centimeters]: mean = 168, median = 167, SD = 10.3, range = 153-197; weight [kilograms]: mean = 67.1, median = 65.9, SD = 13.9, range = 51-118; VO<sub>2max</sub> [mL/kg/min]: mean = 41.4, median = 41.1, SD = 4.94, range = 25.2-55.3). As planned in our Stage 1 registered report, we recruited our participants among UCLouvain students (except from the Faculty of Movement and Rehabilitation Sciences, in order not to interfere with the physical activity programs of the Bachelor/Master of Physical Education and Physiotherapy) who wanted to participate in our start-to-run study. Participants were recruited via flyers with a QR code

directing them to an online screening tool (LimeSurvey platform). The experimenters made announcements in the auditorium (after obtaining the agreement of the Professor in charge of the teaching unit). The online screening tool initially included an informed consent form. An email address and a phone number were provided to allow potential participants to ask questions before agreeing or declining to participate in the study. The screening tool then asked the potential participants (i.e., the ones who agreed to take part in the study) to complete the International Physical Activity Questionnaire (IPAQ; Craig et al., 2003). Since it is a start-to-run program, we recruited individuals corresponding to the low and moderate physical activity categories of the IPAQ. To limit the health risks related to running exercise, each participant was asked to complete the French version of the PAR-Q+ (Warburton et al., 2022) in the presence of one of the two team supervisors (BdG) who has 20 years of exercise testing experience. In the first step, only the first 7 questions of the questionnaire were filled out. Those who answered NO to the first 7 questions of the PAR-Q+ were allowed to participate in the study. Participants who did not meet the study selection criteria (e.g., category high for IPAQ, not signing the informed consent, answering YES to one or more questions of the PAR-Q+) were informed and were not allowed to participate in the start-torun program. Besides, individuals who answered YES to one or more of the questions of the PAR-Q+ were advised to see a (sport) physician.

#### Submaximal exercise test

Before the start of the running program, participants performed a submaximal exercise test (SET) to estimate their Maximal Oxygen Consumption (VO<sub>2</sub>max). The SET consisted of the "1-mile track jog test" (George et al., 1993). During the 1-mile track jog protocol, participants were instructed to run or jog at a self-selected steady, submaximal pace. Because this is a submaximal exercise test, participants were asked not to exceed 80% of their calculated maximal heart rate. The individual maximal heart rate was calculated as: 208 –

 $(0.7 \times \text{age})$  (Tanaka et al., 2001). Participants wore a Polar H10 heart rate monitor which they were asked to check every 250 meters (length of the indoor track). This 1-mile track jog test was validated against a standardized maximal exercise test on a treadmill under laboratory conditions. Oxygen uptake during the laboratory test was measured using a ventilation measurement module (SensorMedics, Yorba Linda, CA). The validation calculation showed a  $r_{adj} = 0.87$  and standard error of estimate = 3.0 mL/kg/min. The 1-mile track jog protocol was specifically chosen because of its resemblance with George and colleagues' (1993) study, namely a running exercise test, the comparable study population: both males and females, a similar age category, and college students. Additionally, this SET was chosen over a maximal exercise test because a submaximal exercise test limits the health risks linked to exercise testing in unfit participants (George et al., 1993). The SET was performed during the first two weeks of October and the first two weeks of December 2023. Participants were contacted in the beginning of March 2024, before the Louvain-la-Neuve 5 Miles running event organized by the university, to take part in an additional SET in order to offer them an index of fitness level progression.

#### Start-to-run program

The primary goal of the start-to-run program was to provide a context that would allow participants to test our hypothesis on the impact of RPE prediction errors on running pleasure across repeated running sessions. As planned in our Stage 1 registered report, the start-to-run program began in the first week of October 2023 and ended on the day of the "Louvain-la-Neuve 5 Miles", which took place on March 20<sup>th</sup>, 2024. The (non-compulsory) end goal of the start-to-run program was that participants take part in this running event. For information, 18 participants (27%) took part in this event.

Participants were asked to undertake weekly "free" running sessions at a self-selected (or preferred) dose. Specifically, participants were encouraged to self-select their running

frequency, intensity, and duration, in which they were allowed to undertake these sessions alone or in groups, where they want. Participants were also allowed to listen to music if they wanted to. These variables (i.e., presence of others and music listening) were recorded and included as covariates in the analysis).

In this start-to-run program, "self-selected" running was thus chosen over "imposed" running. Specifically, when the intensity of physical exercise is self-selected, rather than imposed, it appears to foster a greater sense of autonomy toward physical exercise, and also increased levels of enjoyment and positive affect while exercising (Ekkekakis et al., 2011; Oliveira et al., 2015; Vazou-Ekkekakis & Ekkekakis, 2009). Moreover, because prospective thinking is a crucial factor in maintaining autonomy in daily life (e.g., Blondelle et al., 2022; Kennard & Lewis, 2006), "self-selected" running (i.e., allowing participants to choose the duration, frequency, and intensity of each "free" running session) should also be an optimal approach to facilitate individuals' ability in anticipating the exertion intensity of a forthcoming session of physical exercise, that is, to generate prospective RPE. This approach also fits well with training procedures derived from the ecological dynamic approach to physical exercise behaviors that consider the relationship between individuals' characteristics (e.g., level of physical fitness) and functional aspects of their environment (e.g., running sessions undertaken under multiple contexts).

A key aspect of this start-to-run program was that participants were asked to record each session on a running app called *Formyfit* (<u>https://www.formyfit.com/</u>). Each participant downloaded the Formyfit app on their smartphone and were offered an armband pocket to be able to run with their smartphones. This smartphone app allowed the recording of running session data (while respecting the General Data Protection Regulation, GDPR), including distance, speed, as well as the possibility to collect heart rate data (in the case the participant

ran with a heart rate sensor). Running sessions could be undertaken outdoors or indoors (on a treadmill). For the outdoor session, the GPS of the Smartphone was used to estimate the running distance and speed. When performing an indoor session, the Formyfit app records the time and participants were informed that they had to encode the distance manually in the app at the end of the session. Importantly, since participants were novice or low-frequent runners, the Formyfit app recommended running duration based on participants' VO<sub>2</sub>max (estimated from the SET). These recommendations were made available to the participant on the app and could be downloaded in a document format. The participants were able to choose whether or not they wanted to follow the proposed running duration. Participants had also access to the general Formyfit dashboard app featuring summary information on their running sessions (e.g., frequency, average distance, average speed, and heart rate).

In addition to the free run sessions, participants were invited on a weekly basis to attend a running session supervised by coaches (i.e., 5<sup>th</sup> year Master's degree students in Physical Education at UCLouvain who were involved in the start-to-run program). These coaching sessions occurred at different locations on the Louvain-la-Neuve campus of UCLouvain. This type of session was given in group, but participants were asked to run at their preferred pace (e.g., to walk when they felt the need to do so). These coaching sessions were undertaken without music (i.e., headphones). Different schedules were proposed each week with a maximum of 10 participants per group, and one or two coaches in each group session. Each group session started with a warm-up and ended with a cool-down and stretching routine which was guided by the coaches. The coaches ran with the participants, with one coach running at the front of the group, and the other at the back. This allowed the coaches to supervise the fastest and slowest runners and give personal advice (e.g., advice on running techniques and running stance) during the running session. Participants also received general information on running techniques, nutrition, and sports injury prevention through the

# articles that were available on the Formyfit blog

(http://blog.formyfit.com/category/articlesconseils/nutrition/). Moreover, because selfselected exercise may also increase the odds of adopting inappropriate exercise intensity (e.g., Johnson & Phipps, 2006), participants had the possibility to discuss with the coaches (during the weekly "guided" sessions or by email) how to adjust their "free" running session if needed.

# **Primary measures**

**Prediction error of RPE.** RPE was assessed directly before (prospective RPE) and after (retrospective RPE) each running session on the Formyfit app (see **Figure 1**). Based on Foster and colleagues' approach (2001), participants were asked to provide a prospective or retrospective rating of their RPE of the overall running session (i.e., session RPE). Specifically, as in Foster et al. (2001), we explained to the participants that they had to provide a global rating of the entire running session.

RPE was indexed using the French adaptation of the Borg's Category Ratio-10 (CR-10) RPE scale (Haddad et al., 2013; see also, Foster et al., 2001; Borg, 1998). Specifically, for prospective RPE, participants had to estimate the intensity of exertion ("effort" in French) they expected to feel during the forthcoming running session ("What intensity of exertion do you expect to feel during this session?") on a Likert scale ranging from 0 ("null", "nulle" in French ) to 10 ("maximal", "maximale"), with other integers on the scale assigned modifiers (1 = "very very light" ("très très légère"), 2 = "light" ("légère"), 3 = "moderate" (modérée), 4= "somewhat hard" ("assez dure"), 5 = "hard" ("dure"), 6 = [no verbal anchor], 7 = very hard("très dure"), 8 = [no verbal anchor], 9 = [no verbal anchor]; see**Figure 1A**). Forretrospective RPE, participants had to report the intensity of exertion they experienced duringthe running session ("What intensity of exertion did you feel during this session?") on a scaleranging from 0 (null) to 10 (maximal), with the same integers on the scale assigned modifiers (see **Figure 1B**). Participants did not have access to their prospective RPE during their run or while filling out the retrospective RPE. They were also asked to formulate their retrospective RPE without trying to remember or reflect on their prospective RPE.

Using this in-app procedure, prediction error was operationalized using an *absolute change index* (e.g., Mattes and Roheger, 2020), with prediction\_error = *prospective RPE* – *retrospective RPE* (variable name = absolute\_prediction\_error). For instance, with a prospective RPE of 3 and a retrospective RPE of 5, the RPE absolute prediction error = -2. In this context, a positive prediction error (i.e., the experienced level of exertion is lower than expected) corresponds to a positive score difference, and a negative prediction error (i.e., the experienced level of exertion is higher than expected) corresponds to a negative score difference.

**Retrospective running pleasure.** Retrospective running pleasure (variable name = running\_pleasure) was indexed using a single item adapted from the single-item measure of enjoyment during exercise developed by Stanley and Cumming (2010). Specifically, directly after having completed the retrospective RPE, participants were asked to estimate the level of pleasure they experienced during the overall running session ("What intensity of pleasure did you feel during this session?") on a 7-point Likert scale ranging from 0 ("none at all") to 6 ("extreme"), with other integers on the scale assigned modifiers (1 = "very little", 2 = "slightly", 3 = "moderately", 4 = "quite a bit", 5 = "very much"; see **Figure 1B**).

#### Secondary measures

**Average speed and distance of a running session.** For each running session, the total running distance (variable name = *distance*) and average speed (variable name = *average\_speed*) were recorded with the Formyfit app (see **Figure 1C**). These measures were implemented as covariates in our statistical models.

#### Additional covariates for the effect of the RPE prediction error on running pleasure.

Previous research has shown that running in a group impacts the level of pleasantness of physical exercise sessions (e.g., Xie et al., 2020). Hence, we examined whether running with or without another person during the "free" sessions (running alone vs. running with another person vs. running with more than one person) or running during the coaching session per se modulated the impact of RPE absolute prediction error on running pleasure (variable name = *running\_group*). We also examined whether the degree of familiarity linked to the running route (variable name = *familiarity*) modulated the impact of RPE prediction error on running pleasure. Indeed, individuals might get better at predicting their level of perceived exertion for habitual running trails, which can decrease the impact of RPE prediction error on running pleasure. These data were recorded directly before (Figure 1A) each running session on the Formyfit app by the participant. In addition, because listening to music might modulate the level of perceived exertion during physical exercise (for a review, see Ballmann et al., 2021), and can impact the perceived pleasantness of exercise sessions (Hutchinson et al., 2020). We also examined whether running with music modulates the effect of RPE prediction error on running pleasure (variable name = music). To do so, participants had to report, directly after the running session, whether or not they ran with music (see Figure 1B). Lastly, participants had the option to write a free commentary on the Formyfit app (see Figure 1B).



Figure 1. A. Pre-session measurements. Ai: reporting on the inter-individual nature of the running session (running a free session alone, running a free session with another person, running a free session with more than one person, or running a coaching session); Aii: habit level of the running session (not at all, a little bit, quite well, very much); Aiii: prospective RPE. B. Post-session measurements: Bi: retrospective RPE; Bii: retrospective running pleasure; Biii: use of music while running (yes or no); Biv: free comment option. C: Running session data (total distance, duration, average speed, heart rate).

# Data analysis

To test our hypothesis, we ran linear mixed models (LMM). LMM is a popular alternative to repeated-measures ANOVA analyses in experimental psychology (Magezi, 2015). In looking at the effects of *RPE absolute prediction error* on *running pleasure* in our study, there are three main advantages of adopting an LMM approach over typical repeated-measures ANOVA. First, when using LMM, it is possible to specify random effects (i.e., here participants are treated as nested random factors). Instead of bundling this variance into an error term, LMM partitions the variance that is associated with these differences explicitly. Second, LMM allows to account for individual differences in the effect of a predictor by adding random slopes. In the present study, the size and direction of the *absolute\_prediction\_error* effect on *running\_pleasure* could differ across individuals. Third, by contrast to repeated-measures ANOVA, LMM can handle missing measurements and different numbers of measurements per subject. In the case of this dataset, the number of

running sessions undertaken across the start-to-run program differed between each participant. For these reasons, the LMM approach was more appropriate.

To run the LMM, we used the lme4 package (Bates et al., 2015) and ran the analysis on Jamovi (Version 2.3.21.0). Significance was calculated using the lmerTest package (Kunzetsova et al., 2017), which applies Satterthwaite's method to estimate degrees of freedom and generate *p*-values for mixed models. All predictor variables were grand-mean centered. The model was ran with the fixed effect of *absolute\_prediction\_error*, *average\_speed*, *distance*, *running\_group*, *familiarity*, and *music* with fixed slope (see also section on pilot data for the rationale on the selection of preregistered analyses):

> *running\_pleasure* ~ 1 + *absolute\_prediction\_error* + *distance* + *average\_speed* + *running\_group* + *familiarity* + *music* +(1/participants).

# Pilot data

Between October 2022 and December 2022, we conducted a pilot study to obtain estimates for fixed and random effects and effect sizes. This pilot study also allowed us to pretest the procedure pertaining to the start-to-run program using a beta version of the Formyfit app. These pilot data were obtained on a sample of 19 participants (4 males, 15 females; age (years): mean = 20.8, median = 21, SD = 2.51, range = 18-25; height (centimeters): mean = 170, median = 167, SD = 8.57, range = 160-192; weight (kilograms): mean = 69.5, median = 64.1, SD = 13.4, range = 52-92; VO<sub>2max</sub>: mean = 40.0, median = 41.3, SD = 6.22, range = 29-51). Participants were UCLouvain students who were categorized in the "low" and "moderate" physical activity categories of the IPAQ and reported no contraindications to exercise using the PAR-Q+.

In the first two weeks of October 2022, all pilot study participants undertook the SET (i.e., the 1-mile track jog test) under standard conditions on an indoor 250-meter track. The start-to-run program was similar to the procedure of the main study (i.e., self-selected mode

of running, weekly guided running session), except that: (i) there was no end goal of participating at a running event (i.e., the Louvain-la-Neuve 5 Miles), (ii) the program lasted less than four months (it ended in December, not in March), and (iii) only primary, not secondary, measures were recorded on the beta version of the Formyfit app (i.e., prospective and retrospective RPE, pleasure, total running distance, and average running speed).

This start-to-run program allowed us to obtain pilot data on 19 participants across 228 running sessions (mean of 12.39 running sessions per participant, median = 11.50, SD = 6.51; minimum = 5, maximum = 32). Initially, the total number of recorded running sessions was 261, but 10 sessions were deleted because the running distance was very low relative to the other running sessions (< 1 kilometer), and 23 sessions were deleted due to at least one missing event (i.e., when a participant did not report prospective RPE, retrospective RPE, and/or running pleasure rating). The SET sessions (n = 19) were not used for this primary data analysis.

Using this pilot data set, we ran LMM analysis using the lme4 package (Bates et al., 2015) on Jamovi (Version 2.3.21.0) The results from these analyses are detailed in **Table 1** and illustrated in **Figure 2A**. Only covariate measures on *distance* and *average\_speed* were recorded for the pilot study. We built our multilevel model by adopting the following three-steps sequence:

**Step 1 (null model).** We first ran the null model by including participants as a cluster variable with random effect, and *running\_pleasure* as the dependent variable with the following model specification: *running\_pleasure* ~ (1/participants). This first step in the model indicated that ICC = .21, which means that differences across participants account for about 21% of the variability in individuals' level of running pleasure. As shown in **Table 1**, the intercept variance is .37 and the within-participant variance is 1.38. In short, results provided evidence for a nested data structure that requires multilevel modeling rather than a

single-level data analytic approach. Specifically, an ICC, even as small as .10 (Kahn, 2011), suggests that participants (Level 2 variable) explain the heterogeneity of running pleasure scores. ICC value near zero suggests that a model including Level 1 variables only is appropriate, and, hence, there may be no need to use multilevel modeling (a simpler OLS regression approach may be more parsimonious).

**Step 2.** As a second step in the model-building process, we added the fixed effect of *absolute\_prediction\_error*, *distance*, and *average\_speed* with fixed slope: *running\_pleasure* ~  $1 + absolute_prediction_error + distance + average_speed + (1/participants). Hence, this second step involved testing a random intercept and fixed slope model. In other words, the relationship between running pleasure and RPE absolute prediction error is assumed to be identical across all participants, while also considering the effect of running distance and average speed on running pleasure. We used grand-mean centered scores for our analyses. As shown in$ **Table 1**, results indicated that a 1-unit increase in RPE absolute prediction error is associated with a significant (<math>p < .001) .15 increase in running pleasure (see also **Figure 2A**). Importantly, -2 Log likelihood and AIC values indicated that there is an increased model fit between Step 1 and Step 2 (see **Table 1**).

**Step 3.** As a third and final step, we ran the model with *absolute\_prediction\_error* as a fixed effect with random slope, and *average\_speed*, *distance*, *running\_group*, *familiarity*, and *music* with fixed slope: *running\_pleasure* ~ 1 + *absolute\_prediction\_error* + *distance* + *average\_speed* + (1 + *absolute\_prediction\_error/participants*). This third step involved testing a random intercept and random slope for the variable *absolute\_prediction error*. In other words, it answered the question of whether the relationship between RPE absolute prediction error and running pleasure varies across participants. We observed a similar effect of absolute prediction error on running pleasure. Specifically, -2 Log likelihood and AIC values indicated that there is no increase in model fit between Step 2 and Step 3 (see **Table** 

1). Moreover, the random effect variances were close to zero, which indicates that there is little variance to be accounted for in the random slope in the data (Rights and Jason, 2019). Hence, these findings suggested that the relationship between RPE prediction error and running pleasure does not vary across participants.

Taken together, the pilot findings provided a preliminary step in the validation of our hypothesis, by showing that RPE prediction error significantly impacts the level of pleasure experienced during a running session. These findings are important as they not only offer preliminary support for the hypothesis of the study but also suggest that the model with random intercept and fixed slope (i.e., step 2) is the best model. Indeed, the model with random intercept and random slope (i.e., step 3) does not result in a better fit. Hence, the step 2 model was selected as preregistered analyses.

# Sample size estimation

To estimate the sample size of the main study, we used the R package smir on the pilot data. In line with recent guidelines that suggest running power analysis based on the lowest meaningful estimate of the effect size (Dienes, 2021), we ran 1000 simulations with a one-unit change on the raw scale of RPE absolute prediction error predicting a raw slope of 0.09 units increase of running pleasure. Specifically, to run our power analysis with the lowest meaningful estimate of the effect size, we decided to use the bottom limit of the 80% confidence interval on the raw slope of absolute prediction error (0.09 to 0.20). This value thus corresponds to 0.09 units increase of running pleasure as effect size of interest. Results indicated that for an alpha of 0.05, the power was .80 (95% confidence interval [.78 .83]) with 34 participants across 416 observations. Accordingly, if  $\alpha$  is chosen at .05, with a minimum effect size of .10, and a power of .80 is desired, then a sample of 34 participants along 12 measurement points (i.e., a running session) is required for testing the step 2 LMM presented in the previous section.

	Null (Step 1)	Random Intercept and Fixed Raw Slope (Step 2)	Random Intercept and Random Raw Slope (Step 3)
Variable			
Intercept	4.47*** (0.16)	4.51*** (0.16)	4.51*** (0.17)
Absolute_prediction_error		0.15*** (0.05)	0.14*** (0.05)
Average_speed		0.31*** (0.07)	0.31*** (0.07)
Distance		0.15** (0.05)	0.15** (0.05)
Variance components			
Within-participant	1.38	1.17	1.17
variance			
Intercept variance	0.37	0.43	0.43
Absolute_Prediction_error			0.001
Additional information			
ICC	0.21		
-2 Log likelihood (FIML)	739.78	713.18***	713.16
Number of estimated	3	6	7
parameters			
Conditional $R^2$	0.21	0.42	0.42
Pseudo $R^2$		0.20	0.20
AIC	747.78	725.76	729.16

Table 1. Results of three-steps sequence LMM from the pilot data

*Note:* FIML = full information maximum likelihood estimation; Total number of running sessions = 228, number of participants = 19. Values in parentheses are standard errors. *t*-statistics were computed as the ratio of each regression coefficient divided by its standard error. \*p < .05. \*\*p < .01. \*\*\*p < .001.

#### Results

#### **Pre-registered** analyses

We obtained data on 66 participants across 417 running sessions (mean of 6.33 running sessions per participant, median = 5.00, SD = 5.07; minimum = 1, maximum = 23). Initially, the total number of recorded running sessions was 464, but 33 sessions were deleted because the running distance was very low relative to the other running sessions (< 1 kilometer), and 12 sessions were deleted due to at least one missing event (i.e., when a participant did not report prospective RPE, retrospective RPE, and/or running pleasure rating).

Using this data set, we ran LMM analysis using the lme4 package (Bates et al., 2015) on Jamovi (Version 2.3.21.0) The results from these analyses are detailed in **Table 2** and illustrated in **Figure 2B**. As planned in the Stage 1 pre-registered report, we built our multilevel model by adopting the following two-steps sequence:

Step 1 (null model). We first ran the null model by including participants as a cluster variable with random effect, and running\_pleasure as the dependent variable with the following model specification: running\_pleasure ~ (1/participants). This first step in the model indicated that ICC = .18, which means that differences across participants account for about 18% of the variability in individuals' level of running pleasure. As shown in **Table 2**, the intercept variance is .29 and the within-participant variance is 1.18. These results thus provided evidence for a nested data structure that requires multilevel modeling rather than a single-level data analytic approach.

Step 2: As a second step in the model-building process, we added the fixed effect of  $absolute\_prediction\_error$ , distance,  $average\_speed$ ,  $running\_group$ , familiarity and music with fixed slope:  $running\_pleasure \sim 1 + absolute\_prediction\_error + distance + average\_speed + running\_group + familiarity + music + (1/participants)$ . We used grandmean centered scores on the predictors familiarity, distance, and average\\_speed for our

analyses (*music* and *group* were entered as ordinal predictor). As shown in **Table 2**, results indicated that a 1-unit increase in RPE absolute prediction error is associated with a significant (p < .001) .17 increase in running pleasure (see also **Figure 2B**). We also observed that a 1-unit increase in running distance (in kilometers) is associated with a significant (p < .001) .06 increase in running pleasure.

	Null (Step 1)	Random Intercept and Fixed Raw Slope (Step 2)
Variable		
Intercept	3.77*** (0.09)	4.05*** (0.21)
Absolute_prediction_error		0.17*** (0.03)
Average_speed		-0.002 (0.009)
Distance		0.06* (0.03)
Familiarity		0.08 (0.05)
Music (yes vs. no)		0.02 (0.15)
Running_Group (two persons vs. alone)		0.03 (0.14)
Running_Group (> three persons vs. alone)		0.15 (0.16)
Running_Group (> three persons vs. two persons)		0.12 (0.18)
Variance components		
Within-participant variance	1.18	1.05
Intercept variance	0.29	0.30
Absolute_Prediction_error		
Additional information		
ICC	0.20	
-2 Log likelihood (FIML)	1306.76	1264.08***
Number of estimated parameters	3	9
Conditional $R^2$	0.20	0.29
Pseudo $R^2$		0.09

**Table 2.** Results of two-steps sequence LMM from the registered report, with absolute prediction error as dependent variable

AIC	1312.63	1285.60

*Note:* FIML = full information maximum likelihood estimation. Total number of running sessions = 416, number of participants = 66. Values in parentheses are standard errors. *t*-statistics were computed as the ratio of each regression coefficient divided by its standard error. \*p < .05. \*\*p < .01. \*\*\*p < .001.

# **Exploratory** analyses

As a non-registered complementary analyses, we aimed to examine the impact of a *relative* index of prediction error (e.g., Mattes and Roheger, 2020), where:

 $relative\_prediction\_error = \frac{prospective \ RPE - retrospective \ RPE}{prospective \ RPE}$ 

Absolute and relative indexes of prediction errors complement each other (e.g., Mattes and Roheger, 2020). Specifically, given the same absolute change, the relative change is larger in magnitude if the prospective RPE value is at a higher level than if it is at a lower level. For instance, (i) with a prospective RPE of 3 and a retrospective RPE of 5, the absolute RPE prediction error = -2 and the relative RPE prediction error = -0.33; (ii) with a prospective RPE of 7, the absolute RPE prediction error is still = -2, but the relative RPE prediction error is now -0.40. For both the *absolute* and the *relative* indexes, a positive prediction error (i.e., the experienced level of exertion is lower than expected) corresponds to a positive scores difference, and a negative prediction error (i.e., the experienced level of corresponds to a negative score difference.

We thus ran our *step 2* multilevel model by replacing absolute\_prediction\_error by relative\_prediction\_error: *running\_pleasure* ~  $1 + relative_prediction_error + distance + average_speed + running_group + familiarity + music +(1/participants). As shown in$ **Table 3**, results indicated that a 1-unit increase in RPE relative prediction error is associated with a significant (<math>p < .001) .54 increase in running pleasure (see also **Figure 2C**).

	Null (Step 1)	Random Intercept and Fixed Raw Slope (Step 2)
Variable		
Intercept	3.77*** (0.09)	3.84*** (0.11)
Relative_prediction_error		0.54*** (0.12)
Average_speed		-0.002 (0.009)
Distance		0.06* (0.03)
Familiarity		0.08 (0.05)
Music (yes vs. no)		0.03 (0.15)
Running_Group (two persons vs. alone)		0.03 (0.14)
Running_Group (> three persons vs. alone)		0.19 (0.16)
Running_Group (> three persons vs. two persons)		0.16 (0.18)
Variance components		
Within-participant variance	1.18	1.08
Intercept variance	0.29	0.32
Absolute_Prediction_error		
Additional information		
ICC	0.20	
-2 Log likelihood (FIML)	1306.76	1276.46***
Number of estimated parameters	3	9
Conditional R <sup>2</sup>	0.20	0.28
Pseudo $R^2$		0.06
AIC	1312.63	1296.46

# **Table 3.** Results of two-steps sequence LMM from the registered report, with relative prediction error as dependent variable

*Note:* FIML = full information maximum likelihood estimation. Total number of running sessions = 416, number of participants = 66. Values in parentheses are standard errors. *t*-statistics were computed as the ratio of each regression coefficient divided by its standard error. \*p < .05. \*\*p < .01. \*\*\*p < .001.



**Figure 2.** Fixed effect of absolute prediction error RPE and on running pleasure for the (**A**) pilot study and (**B**) main study. (**C**) Fixed effect of relative prediction error RPE and on running pleasure for the main study. Semi-transparent grey areas indicate the 80% CI of the fixed effect.

#### Discussion

A fundamental observation from the literature on reward processing is that the pleasure response is not solely based on the intrinsic value of the reward but is also largely influenced by the discrepancy between what we anticipate and what we actually receive, that is, a reward prediction error (Schultz et al., 2016; Kieslich et al., 2021). As outlined in the recommendation report of the stage 1 version of the present registered study (Dienes, 2023), our study aimed to test whether reward prediction error, often tested on short acting stimuli, also apply to long lasting episodes, like a session of physical exercise. In other words, could the pleasure experienced during physical exercise be based on the session going better than predicted?

Specifically, in line with the main dynamic pertaining to reward prediction errors, we hypothesized that physical exercise sessions that are experienced with a lower level of perceived exertion than anticipated (i.e., a positive prediction error) should be associated with a higher level of subjective pleasure experienced during physical exercise sessions, and vice versa (i.e., a negative prediction error). To test this hypothesis, we created a novel marker, the RPE-based prediction error, by comparing RPE before (prospective RPE) and after (retrospective RPE) each running session of a start-to-run program. We tested whether RPE-based prediction error (i.e., the difference between prospective RPE and retrospective RPE for each running session) is associated with retrospective running pleasure (i.e., filled out after the running session).

In line with our hypothesis, we observed (in both a pilot study and the registered study) that RPE (absolute or relative) prediction error significantly impacted the level of retrospective running pleasure. Importantly, the impact of RPE prediction error on running pleasure was observed while controlling for the effect of the running distance, average speed of the run, the degree of familiarity with the running route, as well as the presence/absence of

music while running and the presence/absence of other individuals while running. Moreover, participants were asked to undertake "free" running sessions at a self-selected dose (frequency, intensity, and duration) during a start-to-run program. We were thus able to detect an effect of RPE-based prediction error on running pleasure using an ecological experimental setting of physical exercise. Accordingly, these new findings complement well the literature on RPE and physical exercise pleasure (for a theoretical review, see Ekkekakis et al., 2011; for recent studies, see Hartman et al., 2019; Hutchinson et al., 2020, 2023), as it suggests that experiencing less (more) exertion than expected induced a higher (lower) level of pleasure during physical exercise.

#### Implications, limitations, and future directions

Future studies are needed to better understand under which specific physical exercise conditions the effect of RPE-based prediction error on exercise pleasure occurs the most often or is the strongest. Specifically, in the present study, participants had to provide prospective and retrospective ratings of the overall running session. However, it remains possible that the RPE-based prediction error may not be stable across the session of physical exercise. For instance, RPE-based prediction error might be stronger within specific sections of a running trail or at different stages of the run. This research question could be examined by requesting participants to verbally report RPE and pleasure ratings at specific stages of the running session (e.g., beginning, middle, end), and not only before and after the running session ratings. Prospective and retrospective RPE should also relate to each specific stages of the running session (e.g., what intensity of exertion do you expect to feel during the first section of the running trail?). The feasibility of such research procedure could be enhanced by making participants run on the same routes, as it will allow to compare identical running trail sections across participants.

Another caveat of the present study is that we were not able to provide clear evidence for a causal effect of RPE-based prediction error on physical exercise pleasure. Specifically, one component of our index of RPE-based prediction error (i.e., retrospective RPE) was assessed at the same phase as our index of physical exercise pleasure (i.e., retrospective pleasure), that is, directly after the running session. Future studies should thus adopt experimental designs to further test for the causal effect of RPE-based prediction error on physical exercise pleasure.

One such experimental approach is to manipulate humans' ability to predict how they will feel during a future event, i.e., forecasting (Gilbert & Wilson, 2007; Wilson & Gilbert, 2003, 2005). Specifically, while prospective thinking refers to the mental simulation of the future, forecasting refers to prediction of the likelihood of and reaction to events (Pilin, 2021; Wilson & Gilbert, 2003, 2005). Forecasting has been mostly studied in the context of emotional or hedonic events (i.e., affective forecasting; Pilin, 2021). Importantly, studies have shown that affective forecasting can be modulated through framing procedures (e.g., Fu et al., 2018), that is, manipulation of how a situation is presented. For instance, the expected enjoyment of physical exercise is increased when participants consider beginning their routine with their favorite type of exercise and ending with their least favorite exercise (Ruby et al., 2011). However, it is currently unknown whether bodily-oriented forecasting can also be modulated by a framing procedure. Investigating this aspect is important since our index of prediction error features prospective RPE. Accordingly, this line of research should allow to examine whether manipulating "physical effort forecasting" modulates the impact of RPE-based prediction error on experienced pleasure.

Another option is to request participants to increase or decrease their running speed across the running session. Indeed, studies showed that decreasing the effort intensity throughout a running session is associated with greater retrospective pleasure (Brewer et al.,

2000; Fessler et al., 2024; Hutchinson et al., 2020, 2023; Zenko et al., 2016). Accordingly, this type of experimental procedure will allow to examine whether the effect of RPE-based prediction error on running pleasure differ according to the dynamic of effort intensity (i.e., increasing vs. decreasing effort intensity).

It would also be interesting to request participants to run multiple times on the same route (e.g., four running sessions separated by 2 or 3 days). This type of within-subject design (i.e., session 1 vs. 2 vs. 3 vs. 4) should allow researchers to test whether the impact of RPEbased prediction error on running pleasure is modulated by the degree of familiarity toward the running route (i.e., a decrease in the magnitude of the effect of RPE-based prediction error on running pleasure). Indeed, in the present study, the degree of familiarity with the running route was only used as control variable. In other words, the "free" running sessions procedure hampered the experimental manipulation of this variable. It would thus be important to test whether the effect of RPE-based prediction error differ across time (i.e., the repetition of the same running trail). Noteworthy, this type of within-subject design might trigger several learning effects that might be difficult to disentangle. For instance, individuals might get better at predicting their level of physical exertion because they get familiar with the running trail (e.g., they might develop a better pacing strategy over time) and/or because they are getting better in running per se. In this context, this type of study might be better implemented with experienced runners who are running on a new route in order to separate these effects (i.e., compared to neophyte runners, experienced runners should be sensitive to the increase of familiarity with the running route, without significantly improving their level of running expertise).

Finally, while RPE-based prediction error could offer new insight on the experience of pleasure during physical exercise, it is unclear how this novel marker could ultimately lead people to implement physical exercise in their daily-life or continue once they started (with a

coach for example). Put differently, while the experience of pleasure is of key importance for individuals' engagement and commitment to physical exercise (e.g., Teixeira et al., 2022), it remains questionable whether each session of physical exercise should be "calibrated" so that individuals experience higher level of pleasure (i.e., through the experience of positive RPEbased prediction error). Indeed, such type of adaptation may be challenging in people with low cardiorespiratory fitness and/or high body mass index (Bombak, 2014), that is, individuals with low level of physical exercise self-efficacy who might develop life-long avoidance toward physical exercise (Bombak, 2014; Stankov et al., 2012). Specifically, even at low intensity levels (e.g., low running speed or low heart rate), physical exercise sessions can be experienced as strenuous and unpleasant by people with a low cardiorespiratory fitness level (Bombak, 2014), and ultimately linked to repeated experiences of negative RPEbased prediction errors. As a result, experiencing a negative RPE-based prediction error during physical exercise sessions that are initially shaped to foster pleasure or "positive" RPE-based prediction error might actually fuel the belief of people with a low level of fitness that physical exercise is inherently linked to unexpected high levels of physical exertion, which may further decrease the belief in their ability to perform physical exercise (i.e., selfefficacy; Bandura, 1997; Bastianello et al., 2012).

In this context, an alternative strategy is to help individuals to look at difficulties (i.e., negative prediction errors) as challenges rather than threats. This can be learned through the adoption of an "expectation-violation" intervention. Expectation violation is a psychological intervention that requires individuals to focus on the inconsistencies between their expectation and their actual experience (Rief et al., 2022). In the present study, these inconsistencies refer to physical exercise sessions where individuals experience lower or higher levels of physical exercise number of the expectation errors. Importantly, the literature on expectation violation shows that the occurrence of both positive

(i.e., when the situation goes better or less bad than expected) and negative (i.e., when the situation goes worse or less well than expected) prediction error is beneficial, in that it is representative of the large array of situations to be experienced by humans when they expose themselves to challenging situations (Rief et al., 2022). As a result, such intervention should help individuals to look at difficulties (i.e., negative prediction errors) as challenges rather than threats. In other words, they should learn that, even if it's more difficult than expected, they are more capable of managing the difficulty than they thought. This learning process relates to mastery experiences, which are the stronger source of self-efficacy (Bandura, 1997). Therefore, participating to a physical exercise program centered on expectation violation should increase the level of self-efficacy and the commitment toward physical exercise, as compared to start-to-run program without expectation violation intervention.

# Conclusion

This study used a novel marker, the prediction error of RPE, to better understand the conditions under which physical exercise is pleasurable. By assessing prospective and retrospective RPE before and after each running session of a start-to-run program, we observed that the rewarding aspect of physical exercise can be based on the session being less effortful than predicted. This finding should initiate new lines of research to offer fine-grained insight into the hedonic component of physical exercise. This innovative research direction could ultimately lead people to better integrate physical exercise in their daily life.

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