

# **Looking at Affective Forecasting Through the Window of Emotion Regulation**

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### **Abstract**

Recent research has shown that humans often struggle to accurately predict their future emotions. While cognitive biases such as the impact and projection bias are well-documented in affective forecasting, less attention has been given to how individual differences in emotion regulation may influence these forecasts. Emerging literature suggests that emotion regulation, particularly the ability to modulate emotional intensity and duration—may be crucial in reducing forecasting errors. This study investigates the relationship between emotion regulation, operationalized through affect inertia and mean affect levels, and affective forecasting accuracy, aiming to explain what may make some individuals better than others at predicting their own emotions. Using the experience sampling method (ESM), 30 participants reported their positive and negative affect levels five times a day over a 14-day time period. We tested the main and interaction effects of mean affect levels and affect inertia separately for positive (PA) and negative (NA) affect, on forecasting error. Results showed that higher mean NA significantly predicted greater NA forecasting errors, while mean PA was not a significant predictor of PA forecasting errors. Neither inertia nor the interaction between inertia and mean significantly predicted forecasting accuracy for either PA or NA. These results highlight the importance of individuals' average emotional state when considering the accuracy of their affective forecast. Future research should explore how stable personality traits such as neuroticism compare to emotion regulation in shaping forecasting error, as these traits may play a critical role in driving cognitive biases that distort forecasts.

## Looking at Affective Forecasting Through the Window of Emotion Regulation

Think about the last time you experienced an inconvenience and truly believed it would ruin that entire day for you. Looking back at this now, were you able to accurately predict how it would affect your day? Based on current research, the answer is probably not (Takano & Ehring, 2024). Predicting how you will feel in the future - affective forecasting - has gained attention in the literature, and most studies seem to have agreed on one thing: humans are quite flawed when predicting how they will feel in the future. However, while there is this general trend, there are individual differences, with some being better than others at making these predictions (Dunn et al., 2007). We use affective forecasting to guide our behavior throughout our day. We may make a financial decision based on how we believe we will feel, for example spending a lot of money on new clothes thinking it may make us happier when indeed it may not. Thus, there is value in being able to accurately predict how your emotions will unfold throughout the day.

Given that humans often struggle to make accurate predictions about how they will feel, researchers have explored some possible explanations for this phenomenon. Recent literature partially attributes the inaccuracy of affective forecasting to cognitive biases. Takano and Ehring (2024) presented different possible biases that may be involved. Firstly, the *impact bias*, where people overestimate the strength of emotions. Secondly, the *projection bias* in which a person assumes their current emotional state will persist, leading them to predict they will feel the same way in the future. If we all have these biases when making affective forecasts, why are some people better at making forecasts than others (Dunn et al., 2007)?

While we all tend to be affected by these cognitive biases, individuals may differ in their affective forecasting accuracy depending on their emotion regulation ability. Emotion regulation refers to the process in which the individual can influence the type, intensity, and

duration of the emotion (Dunn et al., 2007; Peña-Sarrionandia et al., 2015).<sup>1</sup> Loewenstein (2007) explores the link between affective forecasting and emotion regulation. Affective forecasts rely on current emotions as input, thus individuals who are aware of the influence of emotions on judgment and behavior, and who are skilled at regulating their emotions can mitigate the impact of current emotions on behavior (Loewenstein, 2007). On the other hand, those who struggle with regulation may be more prone to biased forecasts, as they are more influenced by their current affect. Loewenstein (2007) argues that affective forecasting plays a role in all decisions, as we often make choices based on the belief that it will make us happier than the alternative choice would. Therefore, emotion regulation plays a critical role. Understanding this relationship may partially explain individual differences in forecasting accuracy.

In terms of weighing how important emotion regulation strategies may be in making more accurate affective forecasts, Dunn et al. (2007) investigated across two studies whether people with high emotional intelligence are more accurate in their affective forecasts in response to three real-life events. Participants were asked to predict how they would feel in the domains of politics (outcome of the U.S. presidential election), academics (receiving a term paper grade), and sports (their university winning or losing a game). They measured the performance of the participants in four subcomponents of emotional intelligence: perception of emotion, use of emotion to promote thought, understanding emotions and lastly managing emotions. Out of these four subcomponents, managing emotions was found to be the strongest predictor of affective forecasting accuracy (Dunn et al., 2007). This suggests that indeed people who are better at managing their emotions make more accurate predictions. Furthermore, this underscores the importance of exploring how emotion regulation strategies

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<sup>1</sup> The terms emotion regulation and emotion management are used interchangeably in this paper, as both refer to processes through which individuals influence the type, intensity, and duration of their emotions (Dunn et al., 2007; Peña-Sarrionandia et al., 2015).

specifically influence forecasting accuracy instead of examining more broad constructs such as emotion intelligence. Dunn et al. (2007) suggest that this relationship exists because individuals with high emotion management skills understand that emotions are not fixed responses to events but in fact, are influenced by internal strategies (i.e., direction of attention) and external factors (i.e., social support). Thus, similarly to Loewenstein, emotion regulation skills help individuals see the temporariness in their emotions, overcoming certain cognitive biases.

Emotion regulation may be the explanation for these individual differences in forecasting accuracy as the degree of regulation may reduce the negative impact of cognitive biases such as the impact bias. In a study by Kubick et al. (2013) a total of 1,610 participants working in eldercare completed a paper and pencil questionnaire in which, current work-related affect, expected organization changes, predicted work-related affect, and emotion regulation requirements were captured. In this study, emotion regulation was found to moderate the relationship between current affect and predicted work-related affect. In other words, individuals with higher emotion regulation usage are able to better disengage from their current emotional state when predicting their affect in the future, potentially reducing the impact of projection bias. Low emotion regulation usage, on the other hand, makes the current affect more dominant, causing individuals to overestimate the impact of their current emotions on the future, amplifying the impact of biases in prediction (Kubick et al., 2013). This finding illustrates the impact of emotion regulation on affective forecasting by either mitigating or reinforcing cognitive biases. While these findings demonstrate the importance of emotion regulation in moderating bias to improve the accuracy of forecasts, existing literature has approached this by examining how people predict their ability to regulate emotions in addition to affect forecasting, rather than assessing their actual regulatory behavior.

Although self-reports of emotion regulation are linked to worse affective forecasting performance, self-reports might not directly correspond to the actual observable emotion regulation ability (Van Dijk et al., 2016; Dunn et al., 2007; Hoeger et al., 2012). Van Dijk et al. (2016) examined this in a study in which two groups were formed. In one group participants forecasted their emotions and emotion regulation following guilt and shame eliciting situations and the other reported their actual experienced emotions and employed emotion regulation. This study's results demonstrated that forecasters predicted more guilt and shame than the experiencers actually felt, and that forecasters predicted to employ less productive emotion regulation strategies than experiencers actually used. Thus, while these results suggest that self-reports of emotion regulation may be linked to worse affective forecasting, they also shed light on the flaw of using self-reports to measure emotion regulation. It seems that individuals may not be able to gauge their emotion regulation strategies accurately. This highlights the importance of examining real-time regulatory behavior directly, capturing emotion regulation processes across time points.

Previous research on emotion regulation and affective forecasting has not only mainly relied on self-reports but also on single-time-point artificial questionnaires. These methods are limited in capturing the temporal nature of this process, particularly in terms of emotion regulation (Kuppens & Verduyn, 2015). As emotion regulation is a process that occurs throughout time, a singular measurement occasion may not be sufficient to capture this process accurately and reliably. A proposed alternative in the literature that may capture this temporal nature is the experience sampling method (ESM) (Maciejewski et al., 2023; Takano & Ehring 2024). Data in ESM is collected in real-world environments, in which participants complete multiple assessments over time, capturing affect, symptoms, behavior, and cognitions close in time to experience (Moskowitz & Young, 2006; Shiffman et al., 2008).

In the context of ESM, the ability to regulate emotions can be captured through the interplay of affect dynamics, namely, mean and inertia (Kuppens et al., 2010; Maciejewski et al., 2023). The mean describes the average emotional state of the participants while inertia is defined as the carryover of emotion from one moment to the next (Maciejewski et al., 2023). Considering this, emotion regulation is conceptualized based on whether the carryover (inertia) from one moment to the next is considered adaptive, or maladaptive, given the emotion's valence (positive vs. negative) and felt intensity (Koval, Butler, et al., 2015). For example, a prolonged negative state may indicate ineffective regulation while a sustained positive state may indicate effective upregulation, enhancing well-being.

The interpretation of inertia may depend on the individual's mean affect. Maciejewski et al. (2023) propose that the mean affect moderates the impact of affect dynamics on emotional functioning. Supporting this, Bagnara et al. (2025) conducted a mega-analysis of over 70,000 ESM surveys from 948 participants. Their findings show that the adaptiveness of affect inertia depends on the type of emotion being sustained. Specifically, negative affect inertia was partially explained by increases in rumination and suppression, which in turn predicts a further increase in negative affect (NA). In contrast, positive affect predicted greater use of reappraisal, an adaptive strategy that helps sustain positive affect (PA) over time, consistent with the Broaden and Build Theory of Positive Emotions (Fredrickson, 2011).

Thus, taken together, the adaptiveness of affect inertia appears to depend on the typical emotional experience of a person, as the mean indicates the frequency of these experienced emotions. Prolonged negative emotions may be disruptive, as they represent a deviation from a desirable state and are linked to psychological maladjustment (Koval, Brose, et al., 2015), whereas stable positive emotions can be seen as adaptive since they can buffer against negative affect and support well-being (Fredrickson, 2011; Höhn et al., 2013).



Building on this, the current study considers emotional inertia to be adaptive when the individual is experiencing positive emotions, while maladaptive when experiencing negative emotions. Specifically, emotion regulation skilled individuals may exhibit high PA inertia and low NA inertia, allowing positive states to persist, and being able to reduce negative affect. In contrast, those who lack regulation skills may show high NA inertia and low PA inertia, allowing negative states to persist.

To summarize, the following three hypotheses will be examined: 1) Individuals who are better at regulating their emotions, will show low inertia when experiencing negative emotions, and high inertia when experiencing positive ones. 2) Those with poorer emotion regulation skills show the opposite pattern, low inertia when experiencing positive emotions and a high inertia when experiencing negative emotions. 3) Individuals with more adaptive emotion regulation skills, operationalized as having high mean positive affect, high PA inertia, and low NA inertia, are expected to make more accurate affective forecasts, in comparison to those who are not as effective in regulating their emotions.

### **Method**

This research project builds on and partially replicates Takano and Ehring's (2024) study, using the ESM to study affective forecasting accuracy. Participants report and predict their emotions in real time, allowing comparisons between predicted and actual feelings. We extended the study of Takano and Ehring (2024) by including 2-step ahead predictions and interval predictions, to assess both forecasting accuracy and affect uncertainty. However, the 2-step ahead and interval predictions will not be used as they are not within the scope of this research question. While Takano and Ehring (2024) compared the accuracy of the human prediction to a model (Kalman filter) we explore whether the emotion regulation as captured by the affect dynamics has an impact on the forecasting error.

### **Participants**

As we aimed to replicate and extend the study of Takano and Ehring (2024) we aimed for a sample size of 68 participants. The final sample consisted of 30 first-year psychology students from the University of Amsterdam (20 women [66.7%], 10 men [33.3%];  $M = 19.97$ ,  $SD = 4.08$ ; see Appendix A). The study was advertised via flyers on campus, social media, and the student research portal. We therefore used a convenience sample for our study.

## **Procedure**

To be eligible for this research project, students had (a) to own a smartphone, (b) understand the English language, and (c) not have been diagnosed with depression or anxiety. Participating in research projects is part of the curriculum at their university, thus students received course credit for participating in this study. The study was ethically approved (FMG-12534\_2025), and consent was received through a Qualtrics questionnaire. Participants were asked to fill in some demographical information after giving their consent and once this step was completed students were then linked to the m-path app.

The survey was created and conducted via m-path, a flexible survey platform used for repeated mobile assessments (Mestdagh et al., 2023). Using the m-path website, the survey was created, and the participants then used the m-path app to do the repeated measurements. The app is user-friendly, free, and available both on the Android and Apple store, all participants downloaded the app on their personal phones. Participants needed a connection to the internet or mobile data in order to receive notifications to fill out their survey. If participants received a notification but then turned off the WIFI/data while filling out the survey, the answers would not be loaded/gathered (Mestdagh et al., 2023).

The ESM questionnaire focuses on four core emotions: happiness, relaxation, sadness, and anxiety. For each emotion, participants using a visual analog scale filled out both point and interval prediction questions about how they currently feel and were also asked to provide point and interval predictions for the next and subsequent beep.

## Materials

Participants received five prompts per day over a 14-day period to complete the ESM questionnaire. These were sent at fixed times, starting at 9:00 am, and then every three hours until 9:00 pm. In total, the questionnaire could be filled out five times per day. The questionnaire takes around 5-10 minutes to complete. Upon receiving a notification, participants had a 30-minute time window to respond before the prompt expired. While the question sequence remained constant, the order in which the emotions (happy, sad, anxious, relaxed) were presented was randomized each time.

Following the approach of Cloos et al. (2023), we selected happiness and relaxation as indicators of positive affect, and sadness and anxiety as indicators of negative affect. We investigated participants' current emotional state by asking them: “How [emotion] do you feel at the moment?” for each emotion on a visual analog scale from 0 (*not at all*) to 100 (*extremely*). For the one step ahead prediction, participants were asked to fill in the prompt “My best guess is that I will be ... [emotion] ” on a visual analogue scale from 0 (*not at all*) to 100 (*extremely*).

## Data Preprocessing

All data preprocessing was performed in R (v. 4.5.0 R Core Team 2025) and participants with less than 30% compliance (i.e., 21 beeps) were excluded from the dataset to ensure that our data analysis aligns with Takano and Ehring (2024). The overall completion rate of the questionnaires in our dataset is 74% ( $SD = 18.42\%$ ), with an individual compliance range of 31.43% to 95.71%. Moreover, we excluded one participant as they did not reach the compliance criteria, leaving us with 29 participants.

To calculate our measures of emotion regulation from the ESM data, we followed the procedure outlined by Maciejewski et al. (2023). Positive affect was computed as the average of the “happy” and “relaxed” ratings, while negative affect (NA) was computed as the

average of the “sad” and “anxious” ratings. We then used multilevel autoregressive (AR(1)) models to estimate both mean affect levels and affect inertia for PA and NA. In these models, the current affect rating is predicted by the previous rating, with the intercept representing the average affect level and the slope indicating the degree of inertia, or the extent to which affect persists over time (Jongerling et al., 2015). The models were fitted using the brms package (v2.22.0; Bürkner, 2021). Finally, prediction error was calculated as the absolute difference between the observed and predicted affect at each time point.

## **Analysis**

The main analysis was conducted using two separate linear mixed models (LMMs), one for positive affect and one for negative affect, implemented with the lme4 package in R (v1.1.37; Bates et al., 2015). Each model included mean affect, affect inertia and their interaction as fixed effects to examine their influence on participants’ forecasting errors. To account for individual differences, random intercepts for Participant ID were included. Furthermore, correlational analysis was conducted to observe patterns of inertia and mean in emotion regulation.

As the model assumptions of the linear mixed model were violated (see more in the results section), generalized linear mixed models (GLMMs) were additionally conducted with the lme4 package (v1.1.37; Bates et al., 2015). In the GLMM we do not assume a normal outcome distribution. Thus, we use a gamma distribution, and a log-link function to ensure that the output is positive while being able to account for positively skewed data (Ng & Cribbie, 2017).

## **Results**

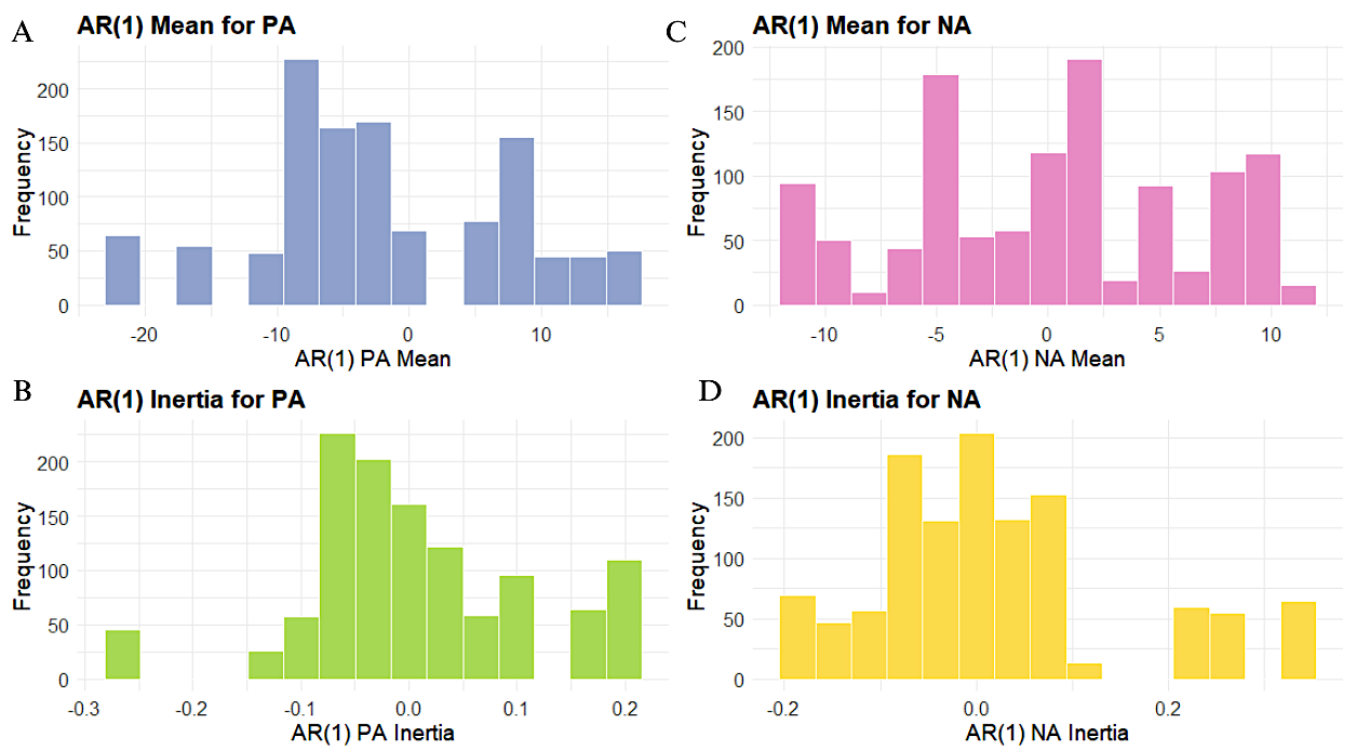
### **Descriptive Statistics**

Figure 1a and 1c visualize the distribution of random effects for the mean, while Figure 1b and 1d show the random effects of the inertia from the sample. To examine how

average affect levels relate to inertia, to capture emotion regulation, a series of correlational analyses were performed. The results show that the mean level of positive affect is significantly negatively correlated with PA inertia, ( $r = -.73, p = <.001$ ), NA inertia ( $r = -.77, p = <.001$ ), and NA mean, ( $r = -.28, p = <.001$ ). PA inertia is not significantly correlated to NA mean ( $r = -.05, p = 0.087$ ) but reaches a statistically significant positive correlation with NA inertia ( $r = .55, p = <.001$ ). Lastly, NA mean is not significantly correlated with NA inertia ( $r = -.06, p = .034$ ) (See Table 1).

**Figure 1**

*Histograms Visualizing the Distribution of Affect Mean and Inertia Across Participants*



**Table 1***Correlational Table Between Predictor Variables**Pearson's Correlations*

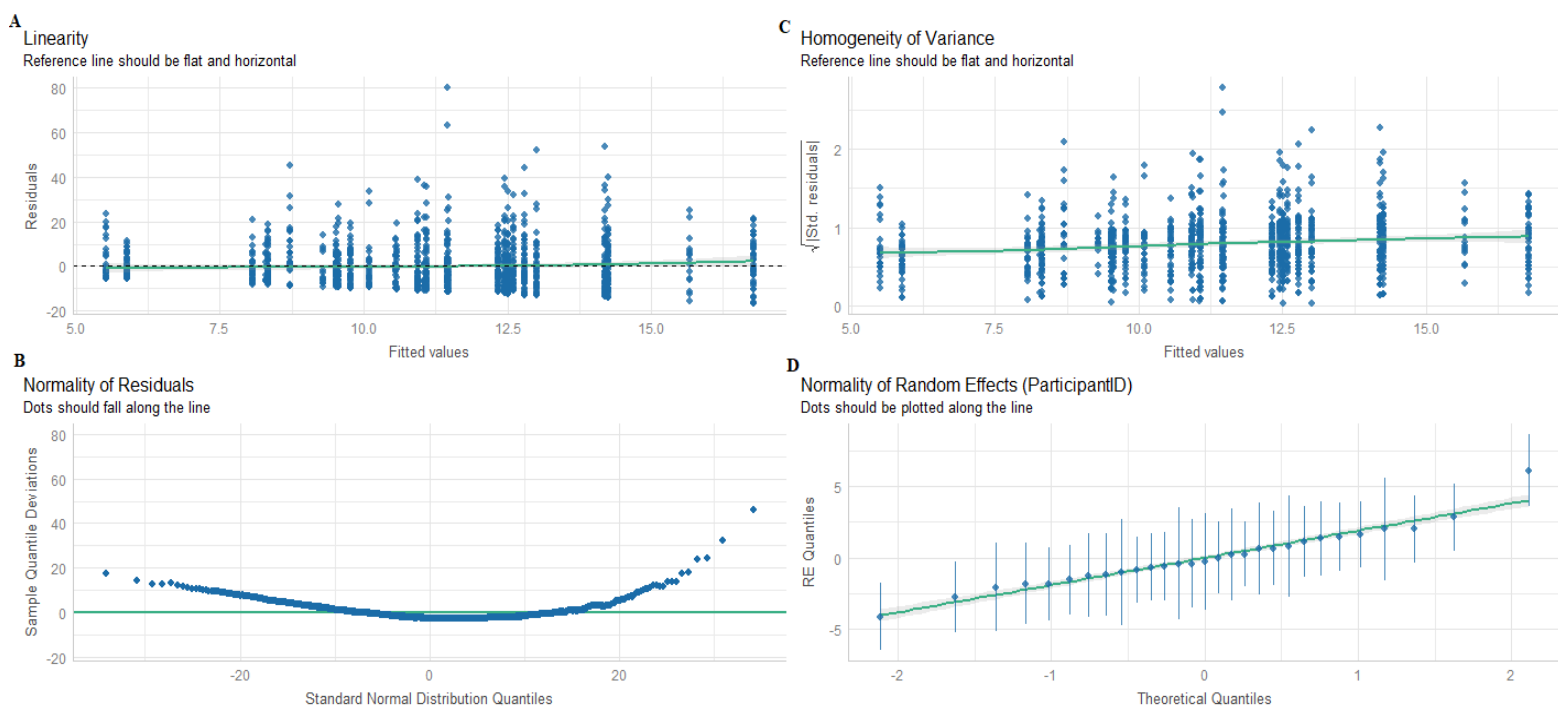
Variable		ar_mod_pa_re_mean	ar_mod_pa_re_inertia	ar_mod_na_re_mean	ar_mod_na_re_inertia
1. ar_mod_pa_re_mean	Pearson's r	—			
	p-value	—			
2. ar_mod_pa_re_inertia	Pearson's r	-0.73	—		
	p-value	< .001	—		
3. ar_mod_na_re_mean	Pearson's r	-0.28	-0.05	—	
	p-value	< .001	0.087	—	
4. ar_mod_na_re_inertia	Pearson's r	-0.77	0.55	-0.06	—
	p-value	< .001	< .001	0.034	—

**Assumption Checks Linear Mixed Model (LMM)**

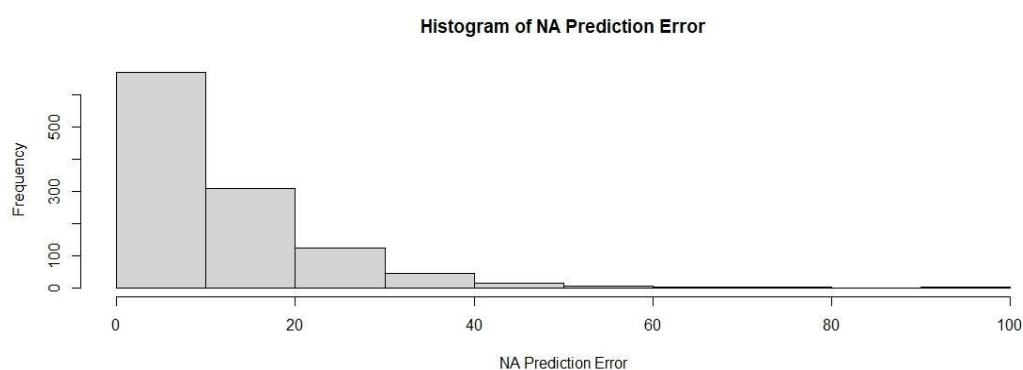
Diagnostic plots indicated that assumptions of normality of residuals and homogeneity of variance are violated for both positive and negative affect. Figures 2b and 4b indicate how the residuals strongly deviate from the line in the normality plots, and the histograms in Figures 3 and 5 reveal a positive skew. Thus, the assumption of normality is not met. Homogeneity of variance is also not met, as seen in the Figure 2c and 4c, the spread of data is not equal across levels of predictors, as shown by the slightly slanted reference lines. However, linearity was approximately met in both models (See Figure 2a and 4a). Lastly, random effects (Participant ID) followed an approximately normal distribution in both models.

**Figure 2**

*Assumption Checks for Linear Mixed Model of Negative Affect, With Fixed Effects, NA Mean and NA Inertia, and Outcome NA Forecasting Error*

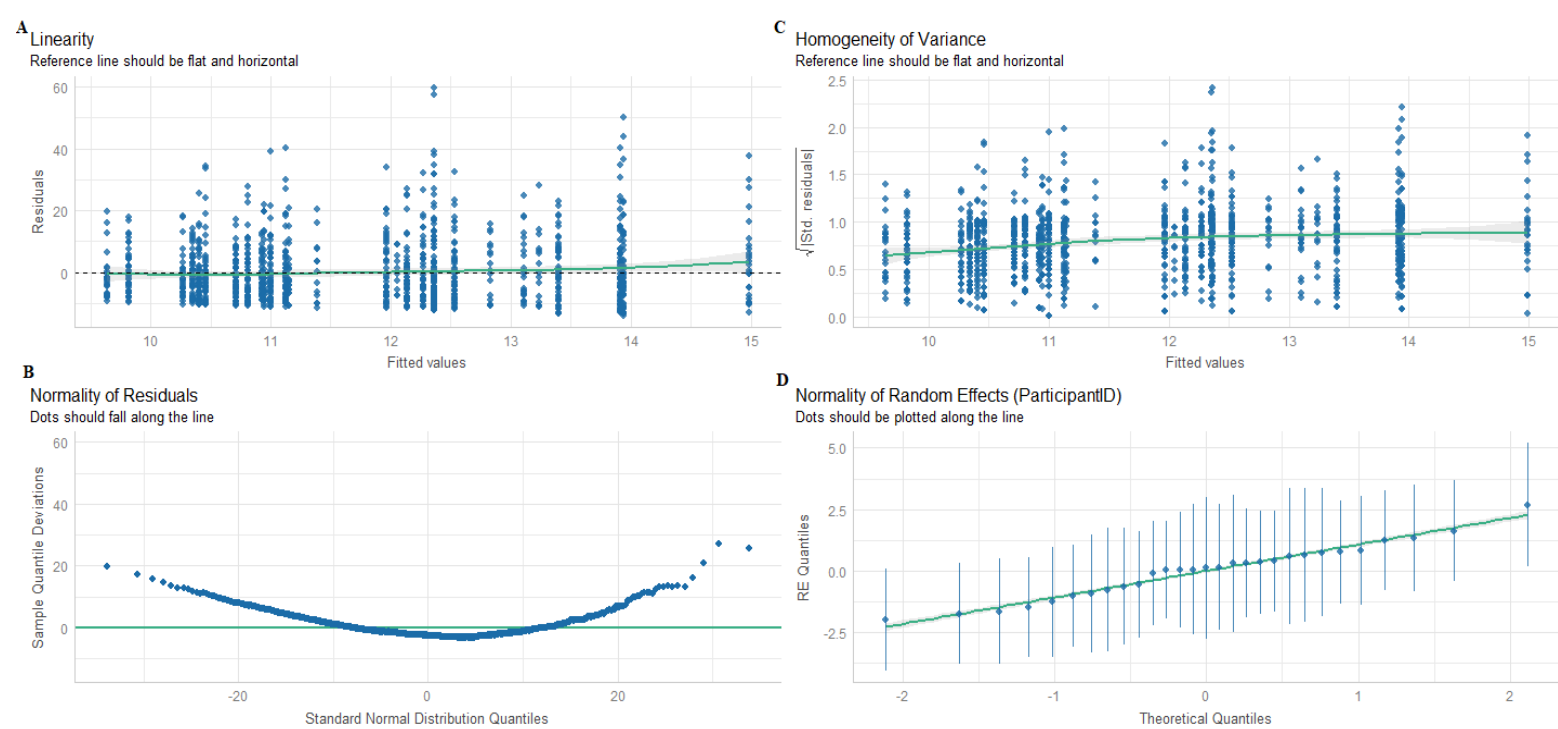
**Figure 3**

*Histogram Visualizing the Distribution of NA Prediction Error*

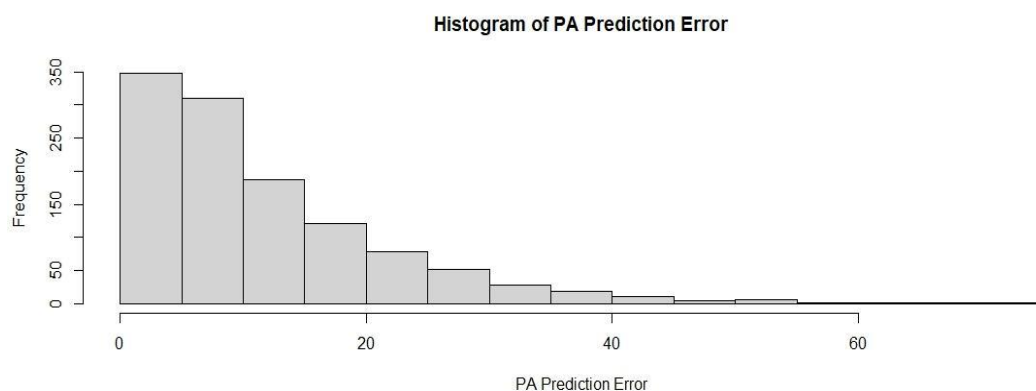


**Figure 4**

*Assumption Checks for Linear Mixed Model of Positive Affect, With Fixed Effects, PA Mean and PA Inertia, and Outcome PA Forecasting Error*

**Figure 5**

*Histogram Visualizing the Distribution of PA Prediction Error*



## Main Analysis

Initially, two linear mixed models (LMM) were conducted separately for positive affect and negative affect to examine the effects of mean affect levels and inertia on



forecasting error. The model included fixed effects for the affect mean and inertia, as well as their interaction, along with random intercepts for Participant ID. Model diagnostics for the LMMs revealed that assumptions of normality and homoscedasticity were violated (See Figures 2-5). Therefore, the model results must be interpreted with caution.

With respect to the model for positive affect, the mean level of PA did not significantly predict forecasting error. ( $B = -0.08$ ,  $SE = 0.07$ ,  $t(23.25) = -1.20$ ,  $p = 0.243$ ). Similarly, PA inertia, had no significant effect on forecasting error ( $B = 0.05$ ,  $SE = 6.28$ ,  $t(22.40) = 0.01$ ,  $p = 0.994$ ), and the interaction between PA mean and PA inertia also failed to reach significance ( $B = 0.37$ ,  $SE = 0.38$ ,  $t(20.67) = 0.97$ ,  $p = 0.343$ ). These findings indicate that neither the average level of positive affect nor its temporal persistence was associated with forecasting error for PA (See Table 2). In simple terms, people who generally felt more positive, or whose positive emotions had a higher carryover, were neither more nor less accurate in predicting how they would feel in the future.

In contrast, the mean NA level significantly predicted forecasting error for negative affect: specifically, a one-point increase in mean NA was associated with a 0.26-unit increase in NA forecasting error. ( $B = 0.26$ ,  $SE = 0.09$ ,  $t(25.22) = 2.84$ ,  $p = 0.009$ ). Neither NA inertia ( $B = 3.08$ ,  $SE = 4.92$ ,  $t(24.10) = 0.63$ ,  $p = 0.537$ ) nor the interaction between NA mean and inertia ( $B = -0.29$ ,  $SE = 0.91$ ,  $t(23.37) = -0.32$ ,  $p = 0.752$ ) reached statistical significance (See Table 3). These results imply that individuals with higher mean levels of negative affect tend to make greater forecasting errors when predicting negative affect, whereas higher mean levels of positive affect or affect inertia do not appear to influence forecasting accuracy for either PA or NA (See Table 2 and 3).

**Table 2***Fixed Effects Estimates From Linear Mixed Model Predicting PA Errors*

Predictor	Estimate	Std. Error	df	t	Pr(> t )
(Intercept)	11.95	0.51	24.46	23.29	<.001***
PA Mean	-0.08	0.07	23.25	-1.20	.243
PA Inertia	0.05	6.28	22.40	0.01	.994
PA Mean $\times$ PA Inertia	0.37	0.38	20.67	0.97	.343

**Table 3***Fixed Effects Estimates From Linear Mixed Model Predicting NA Errors*

Predictor	Estimate	Std. Error	df	t	Pr(> t )
(Intercept)	10.96	0.57	26.33	19.10	<.001***
NA Mean	0.26	0.09	25.22	2.84	.009**
NA Inertia	3.08	4.92	24.10	0.63	.537
NA Mean $\times$ NA Inertia	-0.29	0.91	23.37	-0.32	.752

**Assumption Checks Generalized Linear Mixed Model (GLMM)**

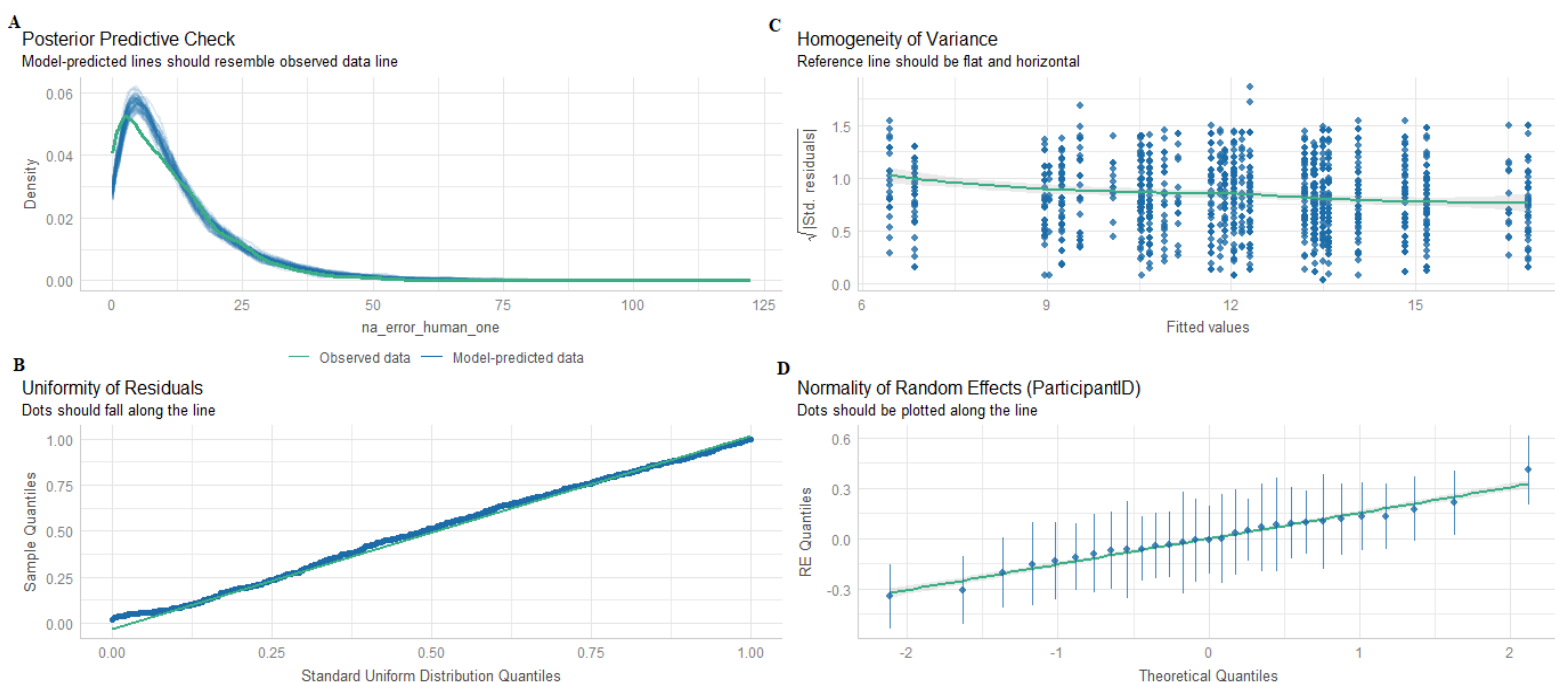
Considering that the model assumptions of the LMM are violated, specifically, the normality of residuals and the homogeneity of variance, an additional analysis using a generalized linear mixed model was conducted as a robustness check.

Posterior predictive checks indicate that the assumed gamma distribution for forecasting errors in both positive and negative affect produces data closely resembling the observed values (Figures 6a and 7a). In each model, the Q–Q plot of residuals shows that points largely adhere to the reference line, with only a minor deviation at the lower tail in the NA model (see Figures 6b and 7b). Both models exhibited mild heteroscedasticity, as indicated by the slightly curved reference lines in Figures 6c and 7c. However, there are no

systematic patterns suggesting that the assumed constant variance is met. Lastly, the random effects for the intercept (based on the Participant ID) followed an approximately normal distribution in both models. Although the NA model showed minor tail deviations, it did not affect inference, supporting the robustness of our findings (see Figure 6d and 7d).

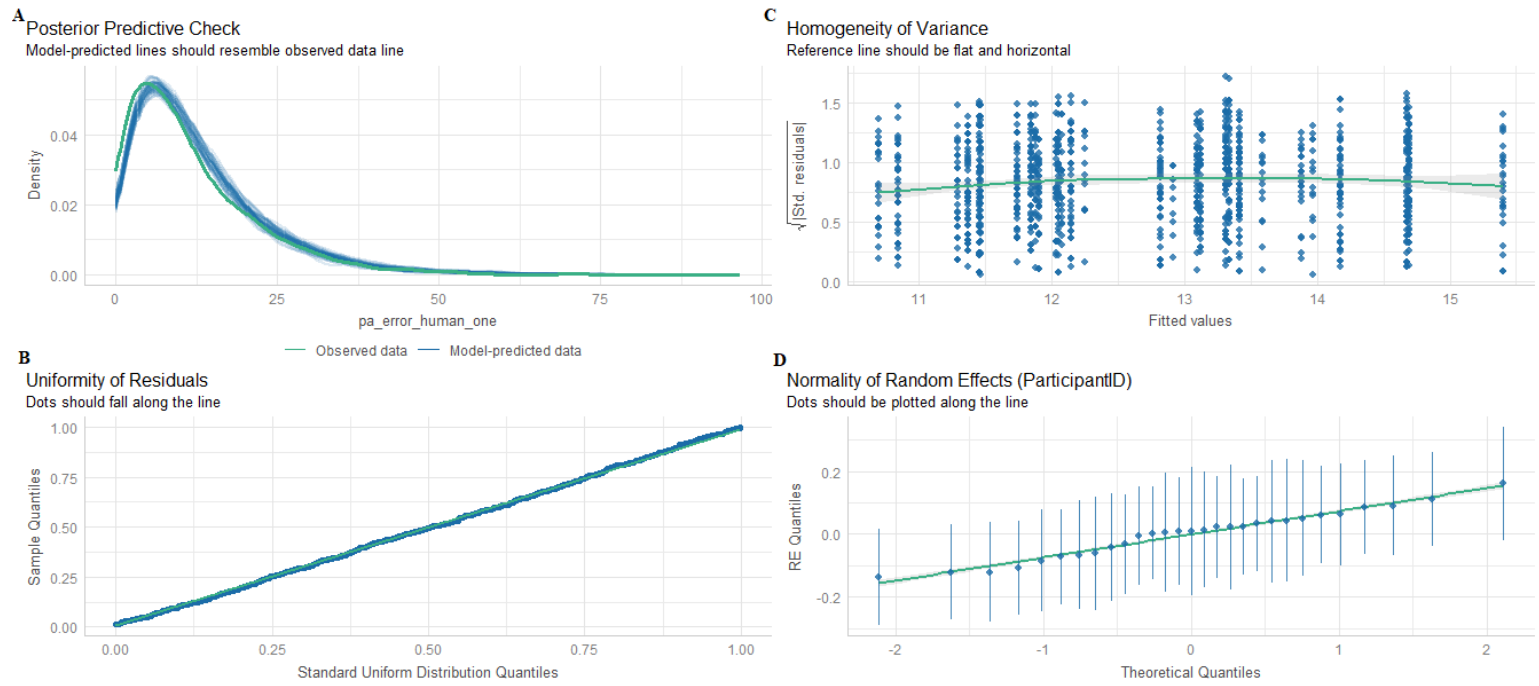
**Figure 6**

*Assumption Checks for Generalized Linear Mixed Models for Negative Affect, With Fixed Effects NA Mean and NA Inertia, and Outcome NA Forecasting Error*



**Figure 7**

*Assumption Checks for Generalized Linear Mixed Models for Positive Affect, With Fixed Effects PA Mean and PA Inertia, and Outcome PA Forecasting Error*



### Adjusted Main Analysis

As the assumptions of the regular LLM were violated we conducted an additional analysis using GLMMs. We fitted the same models as in the main analysis, only changing the outcome type to a gamma distribution with a log-link function. Mean positive affect had no significant effect on forecasting error ( $B = -0.01$ ,  $SE = 0.01$ ,  $z = -1.13$ ,  $p = 0.259$ ). Similarly, PA inertia did not significantly predict forecasting error ( $B = 0.04$ ,  $SE = 0.50$ ,  $z = 0.08$ ,  $p = 0.941$ ), and the interaction between PA mean and inertia also failed to reach statistical significance ( $B = 0.03$ ,  $SE = 0.03$ ,  $z = 0.88$ ,  $p = 0.380$ ) (See Table 4).

As seen in the LMM, mean NA significantly predicted NA prediction error ( $B = 0.03$ ,  $SE = 0.01$ ,  $z = 3.34$ ,  $p < .001$ ), indicating a 2.5% increase in NA forecasting error per 1-unit increase in NA mean when back-transformed ( $\exp(0.025) \approx 1.025$ ). On the other hand, NA inertia did not significantly predict NA forecasting error ( $B = 0.33$ ,  $SE = 0.41$ ,  $z = 0.79$ ,  $p = 0.427$ ), and the interaction between NA mean and inertia failed to reach statistical significance ( $B = -0.02$ ,  $SE = 0.08$ ,  $z = -0.26$ ,  $p = 0.797$ ) (See Table 5). These results confirm

our main analysis, suggesting that only the mean level of negative affect is predictive of a higher forecasting error.

**Table 4**

*Fixed Effects Estimates From Generalized Linear Mixed Model Predicting PA Errors*

Fixed Effect	Estimate	Std. Error	z	Pr(> z )
(Intercept)	2.55	0.04	63.09	< .001
PA Mean	-0.01	0.01	-1.13	.259
PA Inertia	0.04	0.50	0.08	.941
PA Mean $\times$ PA Inertia	0.03	0.03	0.88	.380

**Table 5**

*Fixed Effects Estimates From Generalized Linear Mixed Model Predicting NA Errors*

Fixed Effect	Estimate	Std. Error	z	Pr(> z )
(Intercept)	2.45	0.05	51.06	< .001
NA Mean	0.03	0.01	3.34	< .001
NA Inertia	0.33	0.41	0.79	.427
NA Mean $\times$ NA Inertia	-0.02	0.08	-0.26	.797

## Discussion

The purpose of this study was to examine how emotion regulation skills may be influencing affective forecasting accuracy. Therefore, the following three hypotheses were examined: 1) Individuals who are better at regulating their emotions, will show low inertia when experiencing negative emotions, and high inertia when experiencing positive ones. 2) Those with poorer emotion regulation skills show the opposite pattern, low inertia when experiencing positive emotions and a high inertia when experiencing negative emotions. 3) Those who generally show more competent emotion regulation skills (based on their inertia

patterns) will make more accurate affective forecasts. Starting with hypotheses 1 and 2, surprisingly, positive and negative affect inertia were positively correlated across participants. This suggests that those who showed high positive affect inertia also tended to show high negative affect inertia, which was not expected by the hypothesis. As for hypothesis 3, there was no significant association between inertia (positive or negative) and forecasting accuracy. Furthermore, there was no significant interaction between affect inertia and mean in forecasting error. In other words, a higher carryover of positive affect, which should reflect better emotion regulation, did not lead to more accurate forecasts, even among individuals with generally high levels of positive effect. Likewise, higher carryover of negative affect, which would suggest worse regulation, also showed no clear link to forecasting accuracy. However, one key finding did emerge: individuals with higher mean levels of negative effect (individuals whose baseline affect tended to return to a more negative state), made significantly worse affective forecasts. That pattern wasn't observed for positive affect. Based on these findings, emotion regulation captured through the interplay of mean affect levels and inertia does not predict affective forecasting error but only mean negative affect is associated with worse forecasting than inertia.

To better understand these findings, it is useful to consider how they align or diverge from existing research and theoretical perspectives on emotion regulation and affective forecasting. A strength of this study is that current best practices for measuring emotional regulation were followed using ESM and estimating inertia and mean affect via an autoregressive (AR(1)) model. ESM is well suited to capture emotion regulation while participants engage in their everyday lives, which increases ecological validity (Fritz et al., 2024). The AR(1) regression coefficient quantifies inertia by how strongly a current emotional state depends on the previous one, thus it is suitable to measure both inertia and mean affect (Kuppens and Verduyn, 2015; Maciejewski et al., 2023). However, despite its

widespread use in emotion research, recent work by Albers & Bringmann (2020) argues that such models may oversimplify emotional dynamics by assuming stationarity, meaning that the degree of emotional carryover remains consistent over time. Smith et al. (2023) explore emotion regulation strategies through ESM, they find that emotion regulation strategies used can differ across specific emotions experienced. Moreover, these strategies can vary within individuals across time. This may explain our findings of the unexpected patterns between affect inertia and affect means, as emotion regulation may be too complex to measure over a two-week period. Emotion regulation may fluctuate from day to day basis, and thus measuring it in a time-varying manner may be beneficial (Bosley et al., 2020). We return to this point in the limitations section from a statistical analysis perspective.

Assuming that we did accurately capture emotion regulation processes, we would have to consider how we defined emotion regulation. We hypothesized that individuals who are better at regulating their emotions will show lower inertia when experiencing negative emotions, and higher inertia when experiencing positive ones. Notably, in this study PA and NA inertia were significantly positively correlated with one another, suggesting that individuals who have high inertia in one valence tend to also show this same pattern in the other. Taken together this may support the idea that, high inertia, regardless of valence may reflect a rigidity in emotional responding, narrowing the spectrum of emotions a person can experience (Rottenberg, 2005; Kalokerinos et al., 2020). This is further supported in this study, as individuals with higher PA mean tended to show lower levels of inertia across positive and negative emotions. So contrary to definitions of emotion regulation that equate high PA inertia with better regulation depending on mean affect (Maciejewski et al. 2023), our findings suggest that individuals who in general experience more positive affect may experience more flexible emotion dynamics. Therefore, it may be a lack of inertia across

positive and negative emotions that constitutes adaptive emotion regulation, indicating the necessary flexibility to adapt to situations.

Relating this back to forecasting accuracy, although this study was grounded in prior research suggesting that better emotion regulation – indexed by greater positive inertia and lower negative affect inertia – should enhance forecasting accuracy (Van Dijk et al., 2016; Hoeger et al. 2012; Rizeq and McCann 2019) our findings did not support this theoretical prediction. Given these null findings, we propose an alternative explanation: Certain “forecasting styles” shaped by broader personality traits such as neuroticism may reflect generalized patterns of anticipating emotional persistence (Hoerger & Quirk, 2010). Thus, these stable tendencies may potentially underlie a vulnerability to certain cognitive biases such as the projection and impact bias. While we initially hypothesized that emotion regulation strategies may help individuals mitigate the effects of these biases, it may be that broader personality traits have a stronger influence on the extent these biases appear in individuals. From this perspective, forecasting accuracy may be less influenced by the moment-to-moment regulatory strategies but more by trait-like forecasting tendencies (Dev et al., 2023). This may help explain the lack of main effects of emotion regulation on affective forecasting accuracy.

Our results support this interpretation: individuals with a higher baseline of negative affect exhibited greater forecasting errors for negative emotions, suggesting that trait negativity may bias expectations about future feelings. However, this pattern did not emerge with positive affect. This absence does not necessarily refute the alternative explanation, as prior research indicates that negative emotions tend to exert a stronger influence on forecasting errors than positive emotions (Christophe & Hansenne, 2021). Nonetheless, these findings underscore the importance of further research into the dynamics of positive affect, as this could reveal how certain emotion regulation strategies might reduce forecasting errors,



rather than contribute to them.

### **Limitations and Future Directions**

There are a couple of potential limitations concerning the results of this study. The first limitation concerns the sample size ( $N=29$ ). Although each participant contributed a large number of repeated observations of forecasting error, the key predictors, affective inertia and mean affect, were computed at the between-person level, resulting in a single value per participant. Consequently, the analyses predicting forecasting error were based on between-person comparisons, which limits statistical power for detecting main effects and interactions. Therefore, findings regarding the associations between mean affect, affective inertia, and forecasting error should be interpreted with caution.

Secondly, we conceptualized emotion regulation through inertia and mean affect levels which we obtained from an autoregressive model. The AR(1) model assumes stationarity, in which it assumes that the average value around which an emotion fluctuates and its temporal dependency (i.e., inertia) remains constant over time. As previously mentioned in the discussion section, this may not fully capture the variability in the trajectory of emotional change and regulation (Smith et al., 2023; Bosley et al., 2020). Emotion regulation processes are dynamic and are often described as moment-to-moment processes (Kuppens & Verduyn, 2015). Thus, Albers & Bringmann (2020), suggest a Time-Varying Change Point Autoregressive (TVCP-AR), as it does not assume stationarity, allowing to capture both sudden and gradual changes in inertia within participants. In terms of future research, using TVCP-AR thus may be able to capture the dynamic nature of emotion regulation, giving a more accurate representation of the inner workings of an individual regulating their emotions throughout the day.

Furthermore, while we examined forecasting error for both positive and negative affect, unlike Takano & Ehring (2024), we did not differentiate the direction of the errors. In

other words, we did not capture whether people tended to overestimate or underestimate their future emotions. Clarifying the direction of forecasting error could shed light on mechanisms that maintain negative affect which may be of value for future studies. For example, an overestimation of future positive emotions can lead to negative emotional consequences such as disappointment (Bertoni & Corazzini, 2018). However, the overestimation may also boost resilience until the time point of disappointment (Colombo et al., 2020). On the other hand, the tendency to underestimate future positive emotions can induce pessimism which may negatively impact mood and contribute to a sense of dread about the future (Dev et al., 2023). While both result in increased negative affect, the mechanisms of these differ. Thus, future research should include directionality in affective forecasts as these may shape behavior differently.

Moreover, ESM studies have inherent limitations: because participants choose whether to respond to an experience sampling prompt, intensely distressing emotional states may be underreported (Scollon et al., 2009). For instance, participants who have just received bad news may be less likely to respond during that reporting window.

Lastly, context is absent from our analyses. While we differentiate between maladaptive and adaptive emotion regulation based on patterns of inertia and mean affect, what is considered “adaptive” can depend on the situational context. For example, high emotional negative affect inertia during a stressful time may not necessarily be due to poor emotion regulation – it could simply be a natural response to the stress in the individual’s surrounding environment. Without contextual data, it is difficult to draw certain conclusions about how adaptive a specific emotional pattern is (Paul et al., 2023). Given that ESM captures the participant’s everyday experiences in real time, future research would greatly benefit from including contextual information. This would advance the understanding of emotion regulation in daily life extending to the individual contextual factors.

Despite these limitations, the present study has enhanced our understanding of the relationship between negative mean affect and forecasting accuracy. We hope that the current research will stimulate further investigation of emotion research, particularly the role of emotion regulation behaviors in individuals who present with a high forecasting accuracy.

### **Conclusion**

This experience sampling study sought to capture the emotion regulation processes of individuals throughout their day-to-day lives in order to examine their effects on affect forecasting accuracy. While emotion regulation, operationalized as an interplay of affect mean and inertia, did not significantly predict forecasting error, the study offers value by extending and combining methods from previous papers in affective forecasting research. Notably, it was found that the mean negative affect of individuals predicts negative affect forecasting error. This highlights the importance of the average emotional state that an individual is in when considering the accuracy of their affective forecast. Further refinement in measuring emotion regulation may enhance our understanding of its influence on affect prediction.

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## Appendix A

**Table 1**

*Sample Characteristics (N = 68)*

<b>Age in years</b>	
<b><i>M (SD)</i></b>	19.97 (4.08)
<b>Sex, <i>n</i> (%)</b>	
Female	20, 66.7%
Male	10 33.3%

## Appendix B

### Acknowledgements – AI Disclosure

This report includes content that was generated with the assistance of ChatGPT -4o (<https://chatgpt.com/>). The AI was specifically prompted to aid in my writing using it to improve the wording and spelling. Furthermore, it was used to explain and expand on R codes used in this thesis. Lastly, I used it during the planning stage of my thesis to brainstorm my research question based on my ideas of topic. The AI-generated output was always reviewed and altered by me accordingly.

### *Prompt examples*

The following prompts were input into ChatGPT-4o (<https://chatgpt.com/>):

- 1) “How can I increase the font size of my graph output of the assumption check:

`check_model(mod_pa, check = c("reqq", "linearity", "qq", "homogeneity"), panel = T)”.`

*Output:* The `performance::check_model()` function doesn’t have a built-in argument to directly change font size in its plot output. However, since it returns ggplot-based plots when `panel = TRUE`, you can capture the output and modify the font size using ggplot2 functions.

`# Increase font size in each plot`

```
plots_larger_font <- lapply(plots, function(p) {
  p + theme(text = element_text(size = 16)) # Adjust font size here})
```

*How I incorporated this:* I then this code into my already existing R (see Appendix C) to make the font bigger of the graphs

- 2) “Can you make suggestions, dreading the future, sounds awkward here: On the other hand, the tendency to underestimate future positive emotions can induce pessimism which may negatively impact mood, and cause dreading the future“.

*Output:* You're right — "cause dreading the future" sounds a bit awkward and non-idiomatic. Here's a smoother and more natural revision: **"...and contribute to a sense of dread or anxiety about the future."** Or alternatively: **"...and lead to increased anticipatory anxiety or pessimism about the future."** These options maintain your meaning but sound more polished and academic. Let me know if you'd like it to sound more concise or emotional instead.

*The output was changed by me in the following ways:* I decided to incorporate the wording **“contribute to a sense of dread about the future”**.

*Final version included in thesis:* On the other hand, the tendency to underestimate future positive emotions can induce pessimism which may negatively impact mood **and contribute to a sense of dread about the future.**

- 3) Prompt: Go into the research what so far is being said about bias, emotion regulation and affective regulation with references please

*Output:* Research in psychology has extensively examined the interplay between biases, emotion regulation, and affective forecasting. Here's an overview of key findings:

**Affective Forecasting and Biases:** Affective forecasting refers to predicting one's future emotional responses to events. Studies reveal that individuals often overestimate both the intensity and duration of their future emotions, leading to biases such as:

- **Impact Bias:** The tendency to overestimate the impact of future events on one's emotional state. For instance, people might anticipate feeling happier or more distressed for longer periods than they actually will. [en.wikipedia.org](https://en.wikipedia.org)
- **Durability Bias:** The inclination to overestimate how long emotional reactions will last. This bias can lead to misconceptions about the enduring nature of our feelings following significant events. [pmc.ncbi.nlm.nih.gov](https://pmc.ncbi.nlm.nih.gov)
- **Immune Neglect:** The failure to consider one's psychological coping mechanisms when predicting future emotions. This oversight can result in overestimating the negative impact of adverse events, as individuals often underestimate their resilience. [en.wikipedia.org](https://en.wikipedia.org)

**Emotion Regulation's Role:** Emotion regulation involves strategies individuals use to influence their emotional experiences. Effective emotion regulation can mitigate the discrepancies between predicted and actual emotional responses by:

- **Reducing Affective Forecasting Biases:** By employing adaptive coping strategies, individuals can better align their emotional predictions with real outcomes, minimizing biases like impact and durability biases. [pmc.ncbi.nlm.nih.gov](https://pmc.ncbi.nlm.nih.gov)
- **Enhancing Resilience:** Anticipating one's ability to regulate emotions can lead to more accurate affective forecasts, fostering resilience and well-being. Recognizing that emotions are manageable allows for more realistic predictions of future feelings. [pmc.ncbi.nlm.nih.gov](https://pmc.ncbi.nlm.nih.gov)

**Implications for Well-Being:** Understanding and addressing these biases through effective emotion regulation has significant implications:

- **Improved Decision-Making:** Accurate affective forecasting enables better choices, as individuals can anticipate their true emotional reactions to potential outcomes.  
[thedecisionlab.com](http://thedecisionlab.com)
- **Enhanced Life Satisfaction:** By aligning expectations with likely emotional experiences, individuals can achieve greater contentment and reduce unnecessary stress. [positivepsychology.com](http://positivepsychology.com)

In summary, the interplay between biases, emotion regulation, and affective forecasting is complex. However, cultivating effective emotion regulation strategies can lead to more accurate predictions of future emotions, thereby enhancing overall well-being.

*How I incorporated this:* The prompt was made with the intention of assessing how established these relationships are in research to ensure that if I chose those variables, I would be able to back it up with current literature. I used the links sent by ChatGPT to read on the topic a bit and then I went on to make my search for literature.

## Appendix C

### R code used for the analysis

```
library(dplyr)
library(tidyr)

# PROCESSING

dat_processed <- read.csv("X:/My Downloads/full_predictions.csv")

dat_long <- dat_processed %>%

# here we filter out data points so that we only have datapoints in the set,
# where a human affective forecast and the corresponding actual observation is available
# because otherwise we have missing data and cannot do the analysis
```

```

filter(!is.na(PA_now_point) & !is.na(PA_one_step_point_match)) %>%
mutate(
  # human one step ahead prediction error
  # calculates difference between actual observed affect in that moment
(PA_now_point/NA_now_point)
  # and the human affective forecasting at the previous time point
(PA_one_step_point_match/NA_one_step_point_match)
  pa_error_human_one = abs(PA_now_point - PA_one_step_point_match),
  na_error_human_one = abs(NA_now_point - NA_one_step_point_match),
) %>%

# now we select the variables needed for the analysis of affect and prediction error

select(
  # Participant for grouping variable
  ParticipantID,
  # number of day and beep number per day
  day_n,
  time_n,
  # mean and inertia for positive affect
  ar_mod_pa_re_mean,ar_mod_pa_re_inertia,
  # mean and inertia for negative affect
  ar_mod_na_re_mean,ar_mod_na_re_inertia,

  # now only prediction error of humans for positive and negative affect as our outcome
  pa_error_human_one,
  na_error_human_one
) #>%

# save data for jasp
write.csv(dat_long,"X:/My Downloads/miora_jasp.csv")

library(lmerTest)

# now we fit a mixed effect model

# the outcome is pa_error_human_one as we are interested in predicting the prediction error

# the predictors are ar_mod_pa_re_mean*ar_mod_pa_re_inertia as we are interested in an
interaction
# between the mean affect level and the inertia/autoregressive of a person as this quantifies
emotion regulation ability

# the part (1 | ParticipantID) adds a random intercept for each participant as we denote the
different participants by the ParticipantID
# in practice this means that every person gets their own individual mean level of prediction
error
# for example person A might have an average prediction error of 10 as they are very good -
while person B makes a lot

```

```

library(lme4)
library(effects)
library(sjPlot)

# first we plot the regular models for NA and PA
# need to specify interaction

mod_pa <- lmerTest::lmer(pa_error_human_one ~
  ar_mod_pa_re_mean*ar_mod_pa_re_inertia + (1 | ParticipantID),
  data = dat_long)
summary(mod_pa)

performance::check_model(mod_pa, check = c("reqq", "linearity", "qq", "homogeneity"), panel
= T)

mod_na <- lmerTest::lmer(na_error_human_one ~
  ar_mod_na_re_mean*ar_mod_na_re_inertia + (1 | ParticipantID),
  data = dat_long)

summary(mod_na)

performance::check_model(mod_na, check = c("reqq", "linearity", "qq", "homogeneity"), panel
= T)

# clear normality violations for both ! which makes sense if we look at outcome distributions

hist(dat_long$pa_error_human_one)
hist(dat_long$na_error_human_one)

# OPTION 2: Generalised Linear Mixed Models
# instead we can use a generalised linear model
# instead of assuming a normal outcome distribution, we can use a different distribution
# for the positive skewed outcome like ours the gamma distribution is very fitting

# we add a small constant again as values need to be strictly positive
mod_glmer_na <- glmer(na_error_human_one + 1 ~
  ar_mod_na_re_mean*ar_mod_na_re_inertia + (1 | ParticipantID),
  data = dat_long, family = Gamma(link="log"))

# since we do not have a normal outcome anymore this assumption is dropped
# instead we see whether the generated data from the model matches the actual observations
(pp_check)
# we also check for uniformity of residuals instead
# there is a difference between simulated residuals used in GLM and regular mixed models
# but not important for bachelor thesis

```

```
performance::check_model(mod_glmer_na, panel = T, check =
c("reqq", "pp_check", "qq", "homogeneity"))
```

```
summary(mod_glmer_na)
```

```
mod_glmer_pa <- glmer(pa_error_human_one + 1 ~
ar_mod_pa_re_mean*ar_mod_pa_re_inertia + (1 | ParticipantID),
data = dat_long, family = Gamma(link = "log"))
```

```
performance::check_model(mod_glmer_pa, panel = T, check =
c("reqq", "pp_check", "qq", "homogeneity"))
```

```
summary(mod_glmer_pa)
```

```
#Descriptive Histograms with SD and Mean
```

```
library(ggplot2)
library(gridExtra)
```

```
plot_hist <- function(data, var, title, xlab, color) {
mean_val <- mean(data[[var]], na.rm = TRUE)
sd_val <- sd(data[[var]], na.rm = TRUE)
```

```
ggplot(data, aes_string(x = var)) +
geom_histogram(fill = color, color = "white", bins = 30) +
geom_vline(xintercept = mean_val, color = "blue", linetype = "solid", size = 1) +
geom_vline(xintercept = mean_val + sd_val, color = "blue", linetype = "dashed", size =
0.8) +
geom_vline(xintercept = mean_val - sd_val, color = "blue", linetype = "dashed", size =
0.8) +
labs(title = title, x = xlab, y = "Frequency") +
theme_minimal()
}
```

```
p1 <- plot_hist(df, "ar_mod_pa_re_mean", "AR(1) Mean for PA", "AR(1) PA Mean",
"#8da0cb")
p2 <- plot_hist(df, "ar_mod_na_re_mean", "AR(1) Mean for NA", "AR(1) NA Mean",
"#e78ac3")
p3 <- plot_hist(df, "ar_mod_pa_re_inertia", "AR(1) Inertia for PA", "AR(1) PA Inertia",
"#a6d854")
p4 <- plot_hist(df, "ar_mod_na_re_inertia", "AR(1) Inertia for NA", "AR(1) NA Inertia",
"#ffd92f")
```

```
grid.arrange(p1, p2, p3, p4, ncol = 2)
```

```
#Descriptive Histograms without SD and Mean
```

```
library(ggplot2)
library(gridExtra)
```



```

plot_hist <- function(data, var, title, xlab, color) {
  ggplot(data, aes_string(x = var)) +
    geom_histogram(fill = color, color = "white", bins = 30) +
    labs(title = title, x = xlab, y = "Frequency") +
    theme_minimal()
}

p1 <- plot_hist(df, "ar_mod_pa_re_mean", "AR(1) Mean for PA", "AR(1) PA Mean",
"#8da0cb")
p2 <- plot_hist(df, "ar_mod_na_re_mean", "AR(1) Mean for NA", "AR(1) NA Mean",
"#e78ac3")
p3 <- plot_hist(df, "ar_mod_pa_re_inertia", "AR(1) Inertia for PA", "AR(1) PA Inertia",
"#a6d854")
p4 <- plot_hist(df, "ar_mod_na_re_inertia", "AR(1) Inertia for NA", "AR(1) NA Inertia",
"#ffd92f")

grid.arrange(p1, p2, p3, p4, ncol = 2)

#compliance check

# Ensure dplyr is loaded
library(dplyr)
full_predictions <- read.csv("X:/My Downloads/full_predictions.csv")

# Define total expected responses
expected_responses_total <- 5 * 14 # 70 questionnaires expected per participant

# Calculate individual compliance rates
# Assumes 'data' is your loaded raw data frame (e.g., from data_clean.xlsx)
# and each row represents a potential questionnaire, with 'current_sad'
# being non-NA if the questionnaire was submitted.
individual_compliance_rates_df <- full_predictions %>% # Use 'data_filtered' if that's your
refined dataset
  group_by(ParticipantID) %>%
  summarise(
    ResponsesSubmitted = sum(!is.na(PA_now_point)),
    ComplianceRate = (ResponsesSubmitted / expected_responses_total) * 100
  ) %>%
  ungroup()

# Calculate overall average compliance rate
average_compliance_rate <- mean(individual_compliance_rates_df$ComplianceRate)

# Calculate descriptive statistics for compliance rates
min_compliance <- min(individual_compliance_rates_df$ComplianceRate)
max_compliance <- max(individual_compliance_rates_df$ComplianceRate)
sd_compliance <- sd(individual_compliance_rates_df$ComplianceRate)
median_compliance <- median(individual_compliance_rates_df$ComplianceRate)

```

```

# Print results
cat("Individual Compliance Rates:\n")
print(individual_compliance_rates_df)

cat("\nOverall Average Compliance Rate:\n")
cat(paste0(round(average_compliance_rate, 2), "%\n"))

cat("\nDescriptive Statistics for Compliance Rates:\n")
cat(paste0("Min: ", round(min_compliance, 2), "%\n"))
cat(paste0("Max: ", round(max_compliance, 2), "%\n"))
cat(paste0("SD: ", round(sd_compliance, 2), "%\n"))
cat(paste0("Median: ", round(median_compliance, 2), "%\n"))

cat("\nFull Summary of Compliance Rates:\n")
print(summary(individual_compliance_rates_df$ComplianceRate))

cat("\nDetailed Descriptive Table:\n")
individual_compliance_rates_df %>%
  summarise(
    N_Participants = n(),
    Min_Compliance = min(ComplianceRate),
    Max_Compliance = max(ComplianceRate),
    Mean_Compliance = mean(ComplianceRate),
    Median_Compliance = median(ComplianceRate),
    SD_Compliance = sd(ComplianceRate)
  ) %>%
  print()

```