Supplementary Materials (SM) for:

Low-certainty modals not future tenses cause increased psychological discounting in English relative to Dutch

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1 Additional temporal precision analysis from Study 1

The Study 1 results support the modal hypothesis. They suggest that the English obligation to use low-certainty modals is a factor driving increased discounting, and they find no support for the temporal distance mechanism. However, recent evidence has emerged supporting the temporal precision mechanism that weak-FTR speakers construe future events less precisely than strong-FTR speakers (Ayres, Katz, & Regev, 2023). Could precision effects have been driving the Study 1 results?

To test this, we built the following measure of temporal precision. We regressed subjective temporal distance over odds against, allowing intercepts and slopes to vary grouped by participant, and saved the residuals. To regress out any effects of odds against on subjective temporal distance, we regressed subjective temporal distance over odds against, allowing slopes and intercepts to vary by participant, Table 8 (fixed effects) and Table 9 (random effects). We then saved the residuals and used these to construct a measure of temporal "imprecision".

To test whether increased future tense use in English resulted in more temporal precision, we estimated the following medition model:

$$\begin{aligned} future.tense._{ij} &= \lambda_1 + \alpha lang_i + \kappa_{1q} X_{1qi} + u_{1j} + e_{1i} \\ subj.temp.precision._{ij} &= \lambda_2 + \tau' lang_i + \beta fut.tense_i + \kappa_{2q} X_{2qi} + u_{2j} + e_{2i} \end{aligned} \tag{1}$$

Full model coefficients and Bayesian R^2 equivalents are reported in Table 10 and Table 11.

This allowed us to partial out any effect that the probability factor (odds against) may have had on participant responses in the subjective temporal distance task. We then calculated the standard deviation of these residuals grouped by participant and temporal delay:

$$\sigma_{jk} = \sqrt{\frac{\sum_{n_{jk}} |x_{ijk} - \bar{x}_{jk}|^2}{n_{jk} - 1}} \tag{2}$$

In other words, the standard deviation of subjective temporal distance within each

participant, j, and level of objective temporal distance, k (after regressing out participant-level effects of probability). This measure indicates how closely grouped an individual participant's answers were within each level of temporal distance (across multiple trials for each level of probability). High values indicate less tight grouping (more temporal imprecision), low values indicate tight grouping (more temporal precision). We refer to this measure as temporal imprecision. The temporal precision mechanism predicts that increased relative future tense marking in English should cause lower imprecision. To test this, we calculated mean future tense use across participant and temporal distance level, and conducted a mediation analysis.

English speakers had lower imprecision than Dutch speakers, τ in Fig. 1b, as predicted by the temporal hypothesis. However, the indirect effect was not significant, $Est. = 0.01,\ CI_{90\%} = [0, 0.02],\ pp = .073$. In fact, it went in the opposite to predicted direction. This was because higher future tense use had a significant positive effect on imprecision, β in Fig. 1 (opposite to the prediction of the temporal hypothesis). In other words, participants who used the future tense tended to also have higher (not lower) subjective temporal imprecision. This suggests that, while English speakers may construe future events more precisely than Dutch speakers, these data do not support the prediction that future tense marking causes such increased temporal precision (c.f. Chen, 2013). By ruling out the precision mechanism proposed in the temporal hypothesis, this analysis therefore further supports the modal hypothesis.

2 Robustness checks controlling for future tense as an additional mediator

Recent evidence suggests that the future tense in English encodes high-certainty modality (Robertson, Roberts, Majid, & Dunbar, 2025). This is compatible with the hypothesis that obligate use of the English future would lead to decreased discounting (Robertson et al., 2025), rather than the increased discounting predicted by the temporal hypothesis (Chen, 2013). It is therefore critical to ensure that reported effects of obligatory low-certainty language use in English are not offset by the obligation to use the high-certainty future tense—as well as rule out possible temporal effects via the

future tense. Since Study 1 already includes the future tense, we report future tense mediation effects below for Studies 2 & 3.

2.1 Study 2

To control for potential effects transmitted via the English obligation to use the future tense, we included it as an additional mediator alongside low-certainty modals. It was treated analogously to low-certainty modal verbs, including estimating interaction effects of English proficiency (Table 3). The indirect effect via future tense is given by $(\alpha_4 + \alpha_6 W_2)\beta_2$, which estimates the marginal effect at $\bar{X}$ (since variables are mean-centered). This was non-significant, $Est. = 0.08$, $CI_{90\%} = [-0.07, 0.22]$, $pp = .189$, indicating that obligatory future tense use in English did not have an effect on subjective value in these data. At the same time, all other reported effects via low-certainty modal verbs remained significant while controlling for future tense, i.e. the direct effect of English ($Est. = -0.09$, $CI_{90\%} = [-0.1, -0.07]$, $pp > .999$), the indirect effect via low-certainty modal verbs ($Est. = -0.72$, $CI_{90\%} = [-1.06, -0.39]$, $pp > .999$), and the total effect ($Est. = -1.2$, $CI_{90\%} = [-1.56, -0.85]$, $pp > .999$). This supports the modal hypothesis in two ways. First, once again, we fail to replicate the effects predicted by the temporal hypothesis (i.e. that obligatory future tense in English relative to Dutch use should cause increased discounting and lower subjective value. Second, it demonstrates that the reported effects of low-certainty modal verbs are robust the controls for future tense. If *will* encodes high-certainty modality (Robertson et al., 2025), we would expect to see higher subjective values as a function of its obligate use in English, which would potentially offset the lower subjective values we find via low-certainty modality. However, we find no such effects, indicating low-certainty modals are driving discounting differences per the theory and evidence advanced in the main text.

2.2 Study 3

We performed a similar analysis for Study 3, adding a second mediator for future tense use (Table 5). Again, this was treated analogously to low-certainty modal verbs,

including and interaction with language to estimate independent paths for the effect of future tense on probability ratings in each language. For English, the future tense mediator path is given by $\alpha_3 * (\beta_2 + \beta_4 X_{English=1)}$. This was non-significant, indicting the obligation to use *will* in English did not translate into any differences in probability ratings, $Est. = 0$, $CI_{90\%} = [-0.01, 0.01]$, $pp = .419$. The total affect remained negative, but fell below significance, $Est. = -0.07$, $CI_{90\%} = [-0.16, 0.01]$, $pp = .922$. At the same time, the indirect effect via low-certainty modals $\alpha_1 * (\beta_1 + \beta_6 X_{English=1)}$ remained negative and significant, $Est. = -0.03$, $CI_{90\%} = [-0.07, 0]$, $pp = .968$, indicating the obligation to use low-certainty modals still caused English speakers estimate subjective probability at lower rates, as in the main manuscript. This supports the modal hypothesis by ruling out potential confounding between the English obligation to use low-certainty modals and to use the future tense, which may encode high-certainty notions and might therefore have been expected to impact reported results.

2.3 Conclusions

Future tense mediation effects were added to the path analyses in Studies 2 & 3. In both cases, these paths were non-significant whilst reported effects via low-certainty modals remained, in the main, robust to these additional controls. These analyses confirm the causal account advanced in the main text—that the obligation to use low-certainty modals in English relative to Dutch is responsible for discounting differences between speakers of these two languages. The results do not support either the temporal account, or the hypothesis that *will* encodes high-certainty modality and might therefore offset discounting differences causes by the obligation to use low-certainty modality (c.f. Robertson et al., 2025).

3 Modeling decisions for objective factors of psychological discounting outcomes

In the reported analyses, we use mean-centered, z-scaled days as our measure of temporal distance, and mean-centered, z-scaled odds against as our measure of probability condition. This is unconventional but we do it for a principled reason, which

we explain here. It is unconventional because discounting (whether it is over time or probability) is non-linear. Most approaches have understandably focused on using non-linear regression techniques to establish the shape of discounting functions, e.g. establishing whether hyperbolic (Mazur, 1987) or hyperboloid (Green & Myerson, 2004) functions fit empirical indifference points the best. Our approach is unconventional because we use linear regressions to regress indifference points over objective predictors (time, probability) even though we know that—to some extent—this breaks assumptions of linearity.

This is justified for two reasons. First, throughout analyses we include measures of subjective time (i.e. from the time-slider tasks) and/or subjective probability (accepting that elicited FTR data measure something to do with participants' representations of probability/certainty, which appears to be justified). A critical point is that temporal discounting over subjective representations of time appears to be mostly linear. Using time-slider tasks like the ones we implement, Bradford, Dolan, and Galizzi (2019) show the subjective representations of time appear to follow near logarithmic processes (similarly to psycho-physical perceptions of heat, sound, and light). Apparently non-constant discounting over objective time may be driven by log-scaled relationships between objective and subjective time. Our data support this conclusion; over objective time, subjective time is curvilinear, whereas over log-time the relationship is basically linear, *Fig. 2*. Data are from Study 1. Correspondingly, indifference points over objective time are non-linear, but are approximately linear over subjective time, *Fig. 3*. This suggests that using non-linear regressions over objective time can serve to capture non-linearities in the psycho-physical perception of time.

Our approach is different. We directly measure subjective representations of time and probability and seek to estimate discounting over these. Allowing discounting to be non-linear over objective inputs would make little sense. In fact, in unreported analyses, we trialed modeling non-linearities over objective time using both $log_e(t)$ and t^2, and over objective probability using both $log_e(p)$ and p^2. In general, using $log_e(t)$ and t^2 rendered effects of subjective temporal distance non-significant, and using $log_e(p)$ and

p^2 renders effects of low-certainty language non-significant. This confirms our account that these measures are capturing elements of participants' beliefs about time and probability which may drive non-constant discounting over objective measures. It was therefore appropriate to model discounting over objective time linearly and capture non-linearities via our subjective measures. Inspection of residuals over predicted values in analyses of data from Studies 1–3 suggested that this was generally reasonable. Some non-linearities were present. In particular, the models reported in the main text may underestimate discounting at near delays and low odds against, but overestimate discounting as delays grow longer and odds against grow higher. Nonetheless, violation of regression assumptions appeared to be within tolerable bounds, and the Bayesian methods we use make no assumptions about residual normality so significance inferences were not affected.

The second reason modeling untransformed objective time and probability is justified has to do with generalizability. One of the reasons that using linear models to capture non-linear relationships is problematic is that it makes it impossible to generalize beyond the observed data. However, since we avoid doing this in the main text, this is not really an issue. It would anyway be inappropriate to generalize our findings to other reward amounts and distances since both factors have an impact on discounting rates (Green & Myerson, 2004). In any case, the non-linearities are over objective measures of time and probability, which we do not interpret or analyze in the main text. For these reasons, our modeling decisions are sound.

4 Normalizing model coefficients measured on different scales

In the main text, we report the untransformed model parameters. This means the substantive effect of Xs on Ys via Ms is difficult to interpret. This is because the $X \rightarrow M$ regressions in Studies 1–3 are logistic, while the $M \rightarrow Y$ regressions, are measures without a linking function. Mediation models where all regression are ordinary afford conclusions such as, "the indirect effect meant that English speakers discounted xx more than Dutch speakers as function of using more low-certainty modal verbs". This is

not possible in models like ours which measure outcomes on different scales. This is why we avoid interpreting the extent of indirect effects in the main text.

There are various solutions to this complicated modeling issue, for instance using causally defined effects (Muthén, 2011), or latent variables (Johnson, 2021). A simpler solution is to standardize coefficients before computing path products. This results in changing the measurement scale, which means it would have been necessary to plot direct and total effects separately from indirect effects in the main text. This seemed cumbersome, so we here report our hypothesis testing but with standardized paths estimated. Estimates were standardized in the following way (from Johnson, 2021). All α coefficients which capture $X \rightarrow M$ paths are standardized by:

$$\alpha \frac{SD_x}{SD_m} \tag{3}$$

where SD_x is the observed standard deviation of X and SD_m is the standard deviation of the binary outcome when analyzed with a logit link:

$$SD_m = \sqrt{\alpha^2 + SD_x^2 + \frac{\pi^2}{3}} \tag{4}$$

and all β coefficients were standardized in a similar fashion:

$$\beta \frac{SD_m}{SD_y} \tag{5}$$

However, in this case SD_m is simply the observed standard deviation of the binary mediator M. Finally in Study 1, the $M_2 \rightarrow M_3$ pathway (i.e. $FUT \rightarrow$ *subjective temporal distance*) is normalized following equation 5, by:

$$\delta \frac{SD_{m2}}{SD_{m3}} \tag{6}$$

After these normalization procedures, we checked all path products reported in the main text to ensure than significance was not affected. In no cases was it affected, which indicates the direction and significance of the path products can still be

interpreted, which we do in the main text.

5 Testing the Study 1 results with discounting scores as the mediator

It is important when conducting mediation analyses to test theoretically-plausible alternative specifications (Hayes, 2013). Study 1 involved the analysis of naturalistic data; it is therefore plausible that English speakers discounted more and therefore used more low-certainty language, rather than the other way around. As such, we specified a simple mediation model to test the alternative account that *English* $\rightarrow$ *discounting* $\rightarrow$ *low-certainty language*:

$$\begin{aligned} subj.val._{ij} &= \lambda_1 + \alpha lang_i + \kappa_{1q} X_{1qi} + u_{1j} + e_i \\ log_e(\frac{\pi_{LC_{ijk}}}{1-\pi_{LC_{ijk}}}) &= \lambda_2 + \tau' lang_i + \beta subj.val._i + \kappa_{2q} X_{2qi} + u_{2j} + h_k \end{aligned} \tag{7}$$

where π_{ijk} is the probability that $y = 1$ for low-certainty language (LC); α is the parameter for the effect of language on discounting, τ' s the parameter for the effect of language on the probability of using low-certainty language, and β is the parameter for the effect of discounting on the probability of low-certainty language use. Intercepts, error, control vectors, and random terms are analogous to the Study 1 model in the main text. Parameter estimates are reported in *Table 7*.

The critical question question was whether increased discounting in English resulted in increased low-certainty language use. To test this, we tested the one-tailed hypothesis that $\alpha\beta > 0$. Evidence for this was weak, $Est. = 0.01,\ CI_{90\%} = [0, 0.02]$, $pp = .909$. This analysis indicates that English speakers discounted more as a function of using low-certainty language, not the other way around.

6 FTR-elicitation task guide

In *Table 12* we provide the FTR-elicitation task which was used in Studies 2 and 3. Following Dahl's (1985, 2000) conventions, contexts are given in [brackets]. For Dutch translations, see the FTR-elicitation task Github repository at `https://github.com/cbjrobertson/ftr_questionnaire_master`.

7 FTR-type classifier keyword lists

In this section, we present the class criteria keyword word lists for the main categories of the FTR-type classifier (English: *Table 13*; Dutch: *Table 14*). To keep tables concise, present tense keywords are not displayed. These are the present tense forms for all the verbs in the FTR-elicitation questionnaire so comprise a long list. Interested readers should consult the FTR-type classifier Github repository at `https://github.com/cbjrobertson/ftr_classifier`. Lists include common misspellings.

8 Tables

Table 1

Regression coefficients for mediation analysis in Study 1

path name**	outcome	predictor	name	Est. = OR	estimate	SE	low-95%CI	high-95%$CI^{\dagger}$	
λ_1	low-certainty language (M_1)	Intercept	-	yes	-1.77	0.17	-2.11	-1.43	*
α_1		English	X	yes	1.69	0.17	1.35	2.03	*
κ_1		odds against	-	yes	1.2	0.12	0.97	1.44	*
κ_2		temporal distance	-	yes	0.18	0.12	-0.06	0.41	
κ_3		odds against * temporal distance	-	yes	-0.06	0.12	-0.3	0.18	
λ_2	future tense (M_2)	Intercept	-	yes	-1.21	0.11	-1.43	-0.99	*
α_2		English	X	yes	0.25	0.12	0.02	0.49	*
κ_1		odds against	-	yes	-0.62	0.08	-0.77	-0.47	*
κ_2		temporal distance	-	yes	0.01	0.08	-0.14	0.15	
κ_3		odds against * temporal distance	-	yes	0	0.07	-0.15	0.15	
λ_3	subjective temporal distance (M_3)	Intercept	-		0	0.03	-0.06	0.06	
δ		future tense	M_2		0.01	0.01	-0.02	0.04	
α_3		English	X		-0.01	0.04	-0.09	0.07	
κ_1		odds against	-		0.01	0.01	0	0.03	
κ_2		temporal distance	-		0.64	0.01	0.62	0.65	*
κ_3		odds against * temporal distance	-		0	0.01	-0.01	0.02	
λ_4	subj. value (indif.) (Y)	Intercept	-		19.63	0.46	18.71	20.56	*
τ'		English	X		-0.95	0.65	-2.18	0.31	
β_1		low-certainty language	M_1		-0.97	0.15	-1.27	-0.67	*
β_2		future tense	M_2		-0.05	0.14	-0.33	0.23	
β_3		subjective temporal distance	M_3		-0.19	0.08	-0.34	-0.05	*
κ_1		odds against	-		-4.08	0.05	-4.19	-3.98	*
κ_2		temporal distance	-		-1.47	0.07	-1.61	-1.34	*
κ_3		odds against * temporal distance	-		0.6	0.05	0.5	0.69	*

*Bayesian 95% Credibility Interval (CI) does not contain zero.
Paths which correspond to markup in the main text are in **bold and red.
†Credibility intervals are reported in the main text at 90% because they test one-tailed hypotheses.

8.1 Results

Table 2

Regression coefficients for mediation analysis in Study 2

path name**	outcome	predictor	name	Est. = OR	estimate	SE	low-95%CI	high-95%$CI^{\dagger}$	
λ_1	low-certainty modal verbs (M)	Intercept	-	yes	-3.85	0.18	-4.20	-3.49	*
α_1		English	X	yes	1.51	0.06	1.38	1.63	*
α_2		English proficiency	W	yes	0.17	0.13	-0.09	0.44	
α_3		English * English proficiency	-	yes	0.19	0.06	0.07	0.31	*
κ_1		odds against	-	yes	1.60	0.12	1.37	1.83	*
κ_2		temporal distance	-	yes	-0.01	0.12	-0.24	0.22	
κ_3		item order	-	yes	0.26	0.03	0.21	0.32	*
κ_4		condition order	-	yes	0.02	0.13	-0.22	0.28	
κ_5		odds against * temporal distance	-	yes	-0.02	0.12	-0.25	0.21	
λ_2	subjective value (Y)	Intercept	-		19.28	0.44	18.42	20.12	*
τ'		English	X		-0.50	0.11	-0.71	-0.28	*
β		low-certainty modal verbs	M		-0.41	0.17	-0.75	-0.07	*
κ_6		odds against	-		-4.28	0.06	-4.39	-4.17	*
κ_7		temporal distance	-		-1.23	0.05	-1.33	-1.13	*
κ_8		condition order	-		0.65	0.43	-0.22	1.47	
κ_9		item order	-		0.10	0.05	0.00	0.21	
κ_{10}		odds against * temporal distance	-		0.39	0.05	0.28	0.49	*

*Bayesian 95% Credibility Interval (CI) does not contain zero.
Paths which correspond to markup in the main text are in **bold and red.
†Credibility intervals are reported in the main text at 90% because they test one-tailed hypotheses.

Table 3

Controlling for future tense mediator – Study 2

path name	outcome	predictor	name	Est.=OR	estimate	*SE*	low-95%CI	high-95%CI	
λ_1	low-certainty modal verbs (M_1)	Intercept	-		-3.85	0.18	-4.20	-3.51	*
α_1		English	X		1.51	0.06	1.38	1.63	*
α_2		English proficiency	W_1		0.16	0.14	-0.11	0.43	
α_3		English * English proficiency	-		0.19	0.06	0.07	0.32	*
κ_1		odds against	-		1.60	0.12	1.37	1.84	*
κ_2		temporal distance	-		-0.01	0.12	-0.25	0.22	
κ_3		item order	-		0.26	0.03	0.20	0.32	*
κ_4		condition order	-		0.02	0.13	-0.23	0.27	
κ_5		odds against * temporal distance	-		-0.02	0.12	-0.25	0.21	
λ_2	future tense (M_2)	Intercept	-		-1.21	0.10	-1.41	-1.01	*
α_4		English	X		0.67	0.04	0.59	0.76	*
α_5		English proficiency	W_2		-0.09	0.08	-0.24	0.06	
α_6		English * English proficiency	-		0.03	0.04	-0.05	0.11	
κ_6		odds against	-		-0.66	0.07	-0.80	-0.52	*
κ_7		temporal distance	-		0.03	0.07	-0.12	0.17	
κ_8		item order	-		-0.05	0.02	-0.09	-0.01	*
κ_9		condition order	-		-0.11	0.07	-0.26	0.03	
κ_{10}		odds against * temporal distance	-		-0.05	0.07	-0.19	0.09	
λ_3	subjective value (Y)	Intercept			19.23	0.44	18.37	20.07	*
τ'		English	X		-0.52	0.11	-0.74	-0.30	*
β_1		low-certainty modal verbs	M_1	Yes	-0.36	0.18	-0.71	-0.01	*
β_2		future tense	M_2	Yes	0.12	0.13	-0.15	0.37	
κ_{11}		odds against	-		-4.27	0.06	-4.38	-4.15	*
κ_{12}		temporal distance	-		-1.23	0.05	-1.33	-1.12	*
κ_{13}		condition order	-		0.64	0.41	-0.15	1.43	
κ_{14}		item order	-		0.10	0.05	0.00	0.21	*
κ_{15}		odds against * temporal distance	-		0.39	0.05	0.29	0.50	*

Table 4

Regression coefficients for mediation analysis in Study 3

path name**	outcome	predictor	name	estimate	SE	low-95%CI	high-95%$CI^{\dagger}$	
λ_1	low-certainty modal verbs (M)	Intercept	-	-0.35	0.04	-0.43	-0.26	*
α_1		English	X	0.72	0.06	0.60	0.84	*
κ_1		certainty	-	-0.37	0.02	-0.40	-0.33	*
λ_2	probability construals (Y)	Intercept	-	0.05	0.04	-0.03	0.12	
τ'		English	-	-0.06	0.05	-0.16	0.04	*
β_1		low-certainty modal verbs	M	0.00	0.05	-0.08	0.09	
β_2		English * low-certainty modal verbs	-	-0.06	0.05	-0.15	0.04	
κ_2		per block $\bar{X}$ pixel proportion	-	0.52	0.03	0.46	0.59	*
κ_4		last pic pixel proportion	-	0.08	0.03	0.02	0.14	*
$\kappa_5 s$		block order	-	-0.16	0.02	-0.19	-0.12	*

*Bayesian 95% Credibility Interval (CI) does not contain zero.
Paths which correspond to markup in the main text are in **bold and red.
†Credibility intervals are reported in the main text at 90% because they test one-tailed hypotheses.

Table 5

Controlling for future tense mediator – Study 3

path name	outcome	predictor	name	Est.=OR	estimate	*SE*	low-95%CI	high-95%CI	
λ_1	low-certainty modal verbs (M_1)	Intercept	-		-0.35	0.04	-0.43	-0.26	*
α_1		English	X		0.72	0.06	0.60	0.84	*
κ_1		certainty	-		-0.37	0.02	-0.40	-0.33	*
λ_2	future tense (M_2)	Intercept	-		-0.14	0.05	-0.23	-0.04	*
α_3		English	X		0.24	0.07	0.10	0.38	*
κ_2		certainty	-		0.18	0.02	0.14	0.22	*
λ_3	probability construals (Y)	Intercept	-		0.03	0.04	-0.04	0.10	
τ'		English	X		-0.04	0.05	-0.14	0.06	
β_1		low-certainty modal verbs	M_1	Yes	-0.01	0.05	-0.10	0.08	
β_2		future tense	M_2	Yes	-0.09	0.03	-0.15	-0.03	*
β_3		English * low-certainty modal verbs	-		-0.04	0.05	-0.14	0.07	
β_4		English * future tense	-		0.09	0.04	0.01	0.17	*
κ_3		per block $\bar{X}$ pixel proportion	-		0.53	0.03	0.46	0.59	*
κ_4		last pic pixel proportion	-		0.08	0.03	0.02	0.14	*
κ_5		block order	-		-0.16	0.02	-0.19	-0.12	*

Table 6

Bayesian R^2 equivalents for regressions in Studies 1–4

study	outcome	name	R^2	SE	$Q_{2.5}$	$Q_{97.5}$
Study 1	low-certainty language	M_1	0.44	0.00	0.43	0.44
	future tense	M_2	0.25	0.01	0.24	0.26
	subjective temporal distance	M_3	0.57	0.00	0.57	0.58
	subjective value	Y	0.64	0.00	0.63	0.65
Study 2	low-certainty modal verbs	M	0.39	0.01	0.38	0.40
	subjective value	Y	0.59	0.00	0.58	0.59
Study 3	low-certainty modal verbs	M	0.44	0.02	0.4	0.47
	probability construals	Y	0.51	0.02	0.47	0.53
Study 4	future tense	Y	0.028	0.00	0.027	0.029
	present tense	Y	0.017	0.00	0.016	0.019
	low-certainty modal verbs	Y	0.021	0.00	0.02	0.022

These are a Bayesian adaptation of R^2 following (Gelman, Goodrich, Gabry, & Vehtari, 2018), including spread statistics for values at the 2.5% and 97.5% percentiles.

Table 7

Parameter estimates for Study 1 results with discounting as the mediator

dv	iv	b	SE	l-95% CI	h-95% CI
subjective value	Intercept	19.31	0.44	18.46	20.19
	English	-1.16	0.66	-2.50	0.16
	subjective temporal distance	-0.18	0.08	-0.33	-0.03
	odds against	-4.24	0.05	-4.34	-4.14
	temporal distance	-1.50	0.07	-1.64	-1.37
	item order	0.03	0.05	-0.06	0.13
	odds against * temporal distance	0.60	0.05	0.50	0.70
low-certainty language	Intercept	-1.64	0.18	-2.01	-1.29
	English	1.69	0.17	1.36	2.02
	subjective value	-0.01	0.00	-0.01	0.00
	odds against	1.17	0.12	0.94	1.41
	temporal distance	0.17	0.12	-0.06	0.41
	item order	0.11	0.02	0.07	0.15
	odds against * temporal distance	-0.05	0.12	-0.28	0.17

Table 8

Study 1: Precision Analysis regressing out effects of odds against (fixed effects)

DV	IV	b	SE	l-95% CI	h-95% CI
temporal distance	Intercept	389.58	7.69	374.76	404.75
temporal distance	odds against	-3.13	7.36	-17.39	11.41

Table 9

Study 1: Precision Analysis regressing out effects of odds against (random effects)

DV	IV	b	SE	l-95% CI	h-95% CI
temporal distance	Intercept	389.58	7.69	374.76	404.75
temporal distance	odds against	-3.13	7.36	-17.39	11.41

Table 10

Study 1: Precision Analysis model coefficients

experiment	dv	iv	b	SE	l-95% CI	h-95% CI
Study 1: Precision Analysis	subj. temporal imprecision	Intercept	0.09	0.05	-0.01	0.18
Study 1: Precision Analysis	subj. temporal imprecision	English	-0.18	0.07	-0.32	-0.04
Study 1: Precision Analysis	subj. temporal imprecision	future tense	0.06	0.02	0.02	0.1
Study 1: Precision Analysis	subj. temporal imprecision	temporal distance	0.06	0.01	0.03	0.09
Study 1: Precision Analysis	future tense	Intercept	-0.05	0.05	-0.16	0.05
Study 1: Precision Analysis	future tense	English	0.11	0.08	-0.04	0.26
Study 1: Precision Analysis	future tense	temporal distance	0.01	0.01	-0.01	0.04

Table 11

Study 1: Precision Analysis model Bayesian R^2 equivalents

study	dv	Estimate	SE	Q2.5	Q97.5
Study 1: Temporal Precision Model	subj. temporal imprecision	0.44	0.01	0.42	0.47
Study 1: Temporal Precision Model	future tense	0.53	0.01	0.51	0.55

Table 12

FTR-elicitation questionnaire (English)

question	question number	temporal distance	certainty number
[Q: Should I bring my umbrella? A: Yes...] ...a storm {BLOW IN} this afternoon.	1003	today	70
[Speaking to a friend who fancies Claire: You should come to the party tonight...] ...Claire {BE} there.	1004	today	80
[Q: What do you think about the football this evening?] A: Madrid {LOSE}.	1060	today	90
[Q: What do you think about the match tonight? A: It {BE} hard to say...] ...Arsenal {LOSE}.	1118	today	60
[Q: Should I bring and extra warm jacket? A: It be your decision...] ...it {SNOW} this afternoon.	1119	today	50
[A to B: Bring some sun cream this weekend...] ...it {BE} sunny!	1013	one week	70
[A to B: We should study chapter three for the exam next week...] ...there {BE} a question on it.	1014	one week	80
[A to B: Bring an umbrella to Germany next week...] ...it {RAIN} in Berlin.	1071	one week	90
[A to B: We should definitely study the digestive system for the exam in a week...] ...there {BE} a question on it.	1072	one week	100
[A to B: I would bring your bathing suit this weekend...] ...the temperature {HIT} 45 degrees.	1129	one week	60

Continued on next page...

Table 12 – *FTR-elicitation questionnaire (English) continued*

question	question number	temporal distance	certainty number
[A to B: Don't you think we should study the extra material for next week's test...] ...there {BE} a question on it.	1130	one week	50
[Father to son: Start investing now. In even a month...] ...your money {BE} worth more.	1018	one month	70
[Q: How do you think the commodities markets {ACT} next month?] A: They {RISE}.	1019	one month	80
[Mother to daughter: Put your allowance in a savings account. Next month...] ...it {BE} worth much more.	1076	one month	90
[Q: What is your opinion for oil futures next month?] A: They {RISE}.	1077	one month	100
[Father to son: Dont throw out that action figure. We {GO} to the comic convention next month...]...it {BE} worth something there.	1134	one month	60
[Q: How do you expect the stock markets {BEHAVE} next month? A: It is unclear...] ...they {RISE}.	1135	one month	50
[A to B: The price of gold always goes up in the autumn. Let's invest now...] ... we {MAKE} a profit in a few months.	1028	three months	70
[In the autumn, a weather presenter: Good news for all you skiers out there...] ...we {SEE} a lot of snow in the next few months.	1029	three months	80
[Doctor to patient: This is just stress. I see it all the time. Try to sleep well and get exercise. In a few months...] ...you {FEEL} better.	1085	three months	90

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Table 12 – *FTR-elicitation questionnaire (English) continued*

question	question number	temporal distance	certainty number
[In the spring, a weather presenter: There hasn't been such a sustained series of high pressure systems in years...] ...we {SEE} a lot of nice weather this summer.	1087	three months	100
[Doctor to patient: These results are concerning, but they can be caused by stress. Try to sleep and get some exercise. In a few months...] ...you {FEEL} better.	1143	three months	60
[In the spring, a weather presenter: The broad outlook over the next few months is fairly unstable, but don't give up hope...] ...we {SEE} sunny weather this summer.	1145	three months	50
[Talking about upcoming elections (it is presently July): Don't waste a vote on the liberal party...] ...they {LOSE} in January.	1033	six months	70
[A to B: Don't bother investing in the tech industry...] ...Silicon Valley {CRASH} within six months.	1034	six months	80
[Talking about the winter's upcoming weather (it is presently June): There {BE} a cold current coming from the arctic this year...] ...it {SNOW} a lot this winter.	1090	six months	90
[A to B: Don't bother investing in the China. There is a bubble...] ...it {CRASH}, within six months.	1092	six months	100
[Talking about the winter's upcoming weather (it is presently June): I hear there {BE} a warm current coming up from the tropics...] ...it {MAKE} this winter warm and wet.	1148	six months	60

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Table 12 – *FTR-elicitation questionnaire (English) continued*

question	question number	temporal distance	certainty number
[A to B: Are you sure about investing in Africa? The next six months {LOOK} unstable...] ...it {CRASH}.	1150	six months	50
[(Talking about the world cup) Q: Do you think The Netherlands {ADVANCE} to the finals this year?] A: They {MAKE} it.	1038	one year	70
[Q: What do you think {HAPPEN} in the American elections next year?] A: The Republicans {LOSE}.	1039	one year	80
[Talking about the world cup: Q: Do you think England {ADVANCE} past Brasil in the next round?] A: They {LOSE}.	1096	one year	90
[Q: What do you think {HAPPEN} in the American elections next year? A: Have you seen their candidate play the crowds?] ...the Republicans {WIN}.	1097	one year	100
[Q: Do you think Man U {ADVANCE} to the finals this year? A: They had a weak start, but they are playing well...] ...they {MAKE} it.	1154	one year	60
[Q: What do you think {HAPPEN} in the American elections next year? A: The Republicans have a strong field, but you never know... with the Democrat base...] ...the Democrats {WIN}.	1155	one year	50

Table 13

FTR-type classifier keyword lists (English)

future	verbal-low-cert	verbal-high-cert	other-low-cert	other-high-cert
is going	can	must	is a chance	for sure
are going	may		fairly certain	no chance
am going	could		rates are shakey	100%
going to	coud		likely to	guaranteed to
gonna	might		toss up	definitely
gona	should		predicted to	definetly
gonn	sould		it is unclear if	definately
theyll	ought		has to opportunity	definite
they'll	would		apparently	certainly
i'll	wouls		dubiously	certain
you'll			improbably	certainty
he'll			likely	assuredly
she'll			maybe	assured
we'll			maby	positive
will			mayhap	clearly
wil			chance	doubtless
twill			chanche	indubitably
willbe			50%	indubitable
gonna			50/50	inevitably
wont			risk	infallibly
won't			perchance	irrefutably
shall			perhaps	irrefutable
'll			possibility	necessarily
ll			possible	necessary
youll			possibly	obviously
shell			potentially	obvious
ill			presumably	surely

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Table 13 – *FTR-type classifier keyword lists (English) continued*

future	verbal-low-cert	verbal-high-cert	other-low-cert	other-high-cert
about to			probable	sure
set to			probability	unavoidably
on the verge of			probably	unavoidable
			probaly	undeniably
			probarly	undeniable
			improbable	undoubtedly
			improbability	undoubted
			improbably	unquestionably
			questionably	unquestionable
			seemingly	absolutely
			somewhat	absolute
			supposedly	
			supposed	
			unsure	
			uncertainly	
			feel like	
			not too sure	
			i am not sure	
			not certain	
			not 100% certain	
			in my opinion	
			think	
			thinking	
			thinks	
			thought	
			believe	
			believes	
			believed	
			believing	
			reckon	

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Table 13 – *FTR-type classifier keyword lists (English) continued*

future	verbal-low-cert	verbal-high-cert	other-low-cert	other-high-cert
			reckons	
			reckoned	
			reckoning	
			expect	
			expects	
			expected	
			expecting	
			expectably	
			expectedly	
			aspect	
			doubt	
			doubts	
			doubted	
			doubting	
			suppose	
			supposes	
			supposed	
			supposing	
			guess	
			guesses	
			guessed	
			guessing	

Table 14

FTR-type classifier keyword lists (Dutch)

future	verbal-low-cert	verbal-high-cert	other-low-cert	other-high-cert
ga	kunnen	moeten	in aanmerking komend	wel degelijk
gaat	gekund	moet	niet zeker	100%
gat	kan	moest	zich vast	twijfel er niet
gaar	kun	gemoeten	een maand of vijf	absoluut
gaan	kunt	moesten	50%	alleszins
zal	kon		de kans is	allicht
zullen	mag		niet duidelijk	bepaald
zult	mogen		is er een kans	beslist
zul	vermogen		lijkt erop	definitief
staat op	vermoogd		lijkt alsof	duidelijk
	zou		naar het schijnt	echt
	zouden		aannemelijk	eenvoudigweg
			allichet	essentieel
			bedenkelijk	evident
			blijkbaar	fietelijk
			denkelijk	gedwongen
			kans	gegarandeerd
			geschiktlijkend	glashelder
			hypothetisch	hoogstwaarschijnlijk
			misschien	helder
			msschien	inderdaad
			misscxhien	kennelijk
			mogelijk	klaarblijkelijk
			mogelijkerwijs	logisch
			ongeveer	natuurlijk
			onzeker	nodig
			ogenschijnlijk	noodzakelijk

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Table 14 – *FTR-type classifier keyword lists (Dutch) continued*

future	verbal-low-cert	verbal-high-cert	other-low-cert	other-high-cert
			klaarblijkelijk	normaal
			schijnbaar	ondenkbaar
			twijfelachtig	onmiskenbaar
			veelbelovend	onmogelijk
			vermoedelijk	onomstotelijk
			waarschijnlijk	ontwijfelbaar
			waarschijnljk	onvermijdelijk
			waarschynlijk	onwaarschijnlijk
			waarschijnlijkheid	onweerlegbaar
			wellicht	onwrikbaar
			volgens mij	overduidelijk
			volgens mijn	overtuigend
			houden voor	sowieso
			niet weten	stellig
			neit weet	uiteraard
			weet niet	vanzelfsprekend
			weten niet	vast
			denk	verplicht
			denken	voorgoed
			denkt	werkelijk
			geloven	wis
			gelooft	zeker
			geloof	ongetwijfeld
			meen	toch
			ment	
			menen	
			gokken	
			gok	
			gokt	
			veronderstellen	

Continued on next page...

Table 14 – *FTR-type classifier keyword lists (Dutch) continued*

future	verbal-low-cert	verbal-high-cert	other-low-cert	other-high-cert
			veronderstel	
			veronderstelt	
			vermoed	
			vermoedt	
			vermoeden	
			gehoord	
			horen	
			hoor	
			hoort	
			betwijfel	
			betwijfelt	
			betwijfelen	
			annehm	
			annehmt	
			annehmen	
			verwacht	
			verwachten	
			verwachting	
			wel eens	
			wel	

9 Figures

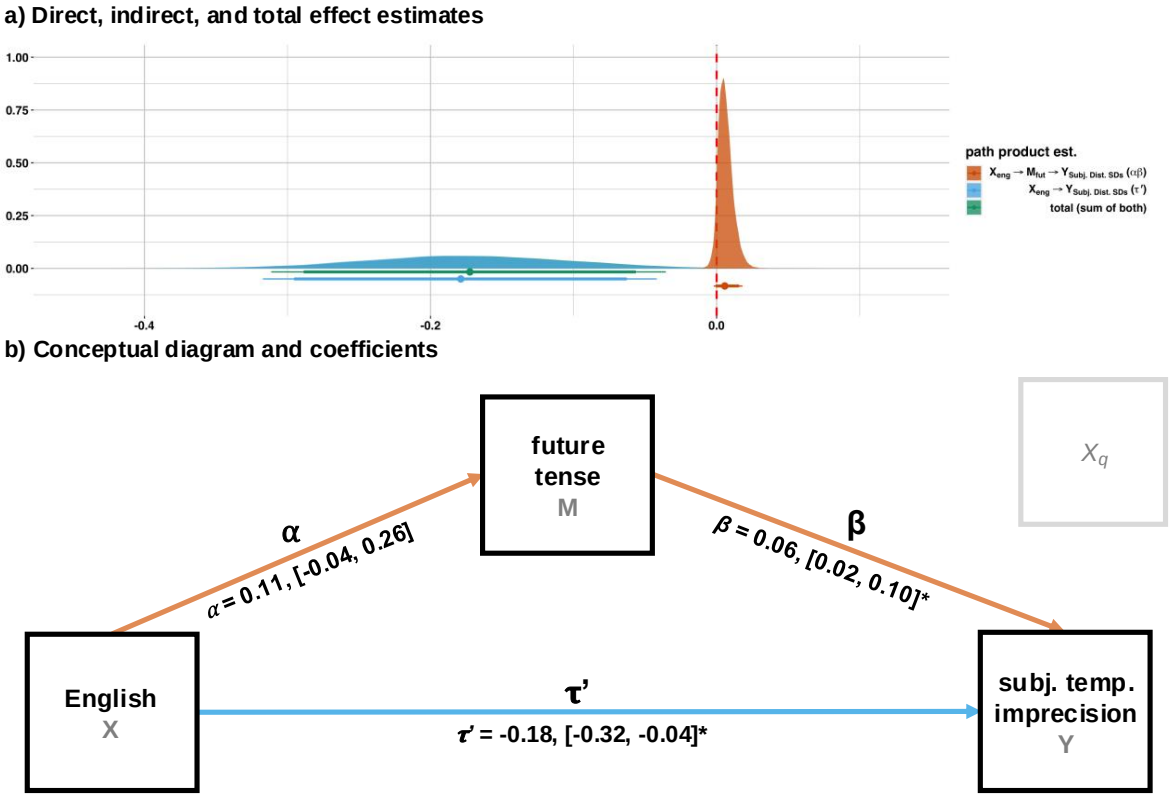

Figure 1. Results from Study 2 analysis of the temporal precision hypothesis. a) Posterior estimates for paths and path products for the effect of speaking English on temporal precision via the future tense. The direct effect is negative and does not contain zero. This suggests English speakers construe future events more precisely than Dutch speakers. However, the indirect effect is not significant, indicating that future tense marking is not causally involved in this effect. b) Conceptual diagram with coefficient estimates. English speakers used more future tense language (α is positive). However, increased future tense language use caused more temporal imprecision (β is positive), which is the opposite direction to that predicted by the temporal precision hypothesis (c.f. Chen, 2013).
*Coefficients for which the 95% CI does not contain zero are significantly different from zero.

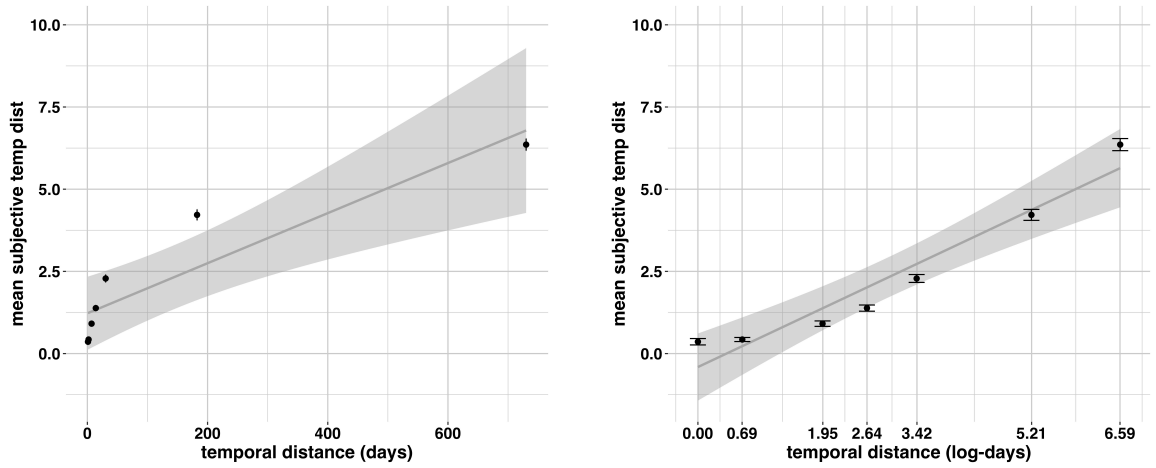

Figure 2. Mean subjective temporal distance ratings ($\pm 1.96SE$) over objective temporal distance in days (left) and in log-days (right) in Study 1, with linear line of best fit.

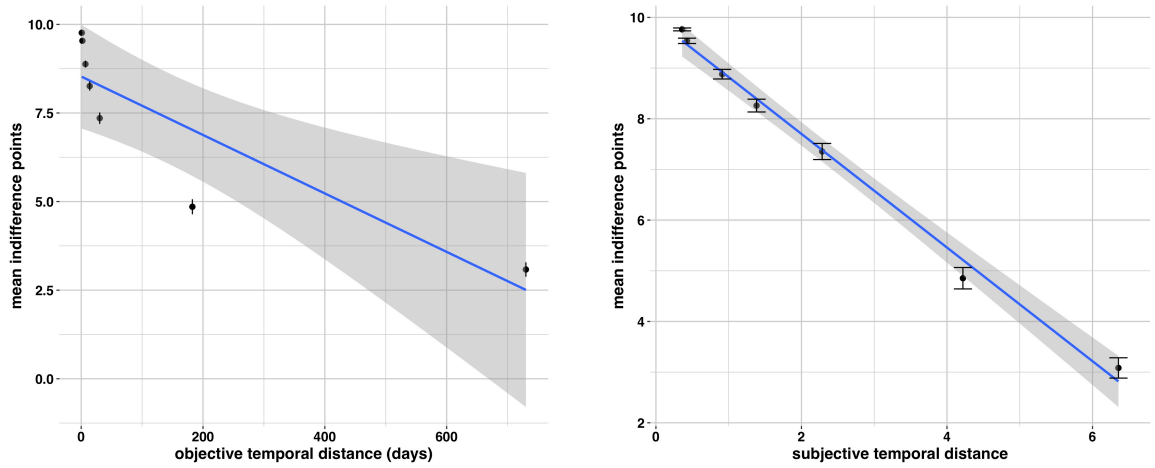

Figure 3. Mean indifference points ($\pm 1.96SE$) over objective temporal distance in days (left) and subjective temporal distance (right) in Study 1, with linear line of best fit.

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