Assessing the ability to resolve linguistic-conceptual conflict

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Abstract

Understanding natural language relies on the cognitive system's sensitivity to shifting contextual demands. We introduce a new behavioral method, inspired by classic cognitive conflict paradigms, that systematically manipulates contextual demands and the semantic association of context-congruent and incongruent word stimuli. In line with the role of spontaneous processes in triggering conceptual conflict, we show that strong semantic links facilitate responses in congruent trials but consistently slow them in incongruent ones. Factor decomposition of reaction times further reveals that identifying congruent and incongruent stimuli engages distinct cognitive capacities.

1 Introduction

Understanding how our minds adapt to the everchanging contextual demands drives contemporary cognitive and language research (Jefferies et al., 2020; Ralph et al., 2017). A commonly experienced phenomenon accompanying shifts in contextual demands is interference from habitual yet contextually inappropriate information that intrudes the current stream of thought (Kühn et al., 2013; Ulrich et al., 2015). A typical scenario highlighting the emergence of conceptual interference may involve sudden changes in contextual nuances of natural language (e.g., when interpreting figurative speech or ambiguous sentences). For example, the meaning of the word "chair" may dramatically change depending on whether we discuss 1) position within a hierarchy (i.e., chair as a position within an organization), 2) furniture for our new kitchen, or 3) dentist visit (i.e., chair as a molar in the Slovak language). Susceptibility to interference from contextually irrelevant information (e.g., thinking of a chair as office furniture when discussing position within an organization) varies naturally in the neurotypical population yet becomes more apparent in thought and language deficits (most notably in aphasias and schizophrenia, Kreher et al., 2007; Lundin et al., 2020; Noonan et al., 2010). The prominent hypothesis regarding these conditions concerns dysregulated controlled mechanisms that fail to detect shifts in contextual demands to signal inhibition of habitual spread of semantic activation onto irrelevant conceptual elements (e.g., Almeida & Radanovic, 2021). However, despite recent advances, this hypothesis lacks evidence from methods that can directly manipulate contextual demands and intensity of semantic interference (or conflict).

In this study, we introduce a novel Context-matching task (CMT), building on traditional cognitive conflict paradigms where controlled and automatic processes compete for response execution (Miller & Schwarz, 2021; Ulrich et al., 2015). The CMT involves systematic manipulation of contextual demands (by including trials where decisions about the relatedness of stimulus and target words are or are not constrained by a context word) and contextual congruency (by including trials where target matches or mismatches the stimulus in a given context). A critical component of the CMT lies in the manipulation of semantic links between the stimulus and target words, which should putatively affect the intensity of semantic interference experienced in contextually incongruent trials where the target relates to the stimulus but not in a specified context (e.g., in a trial such as *doctor*[stimulus] + *dress*[context] = *drug*[target], the target links strongly with the stimulus but not with the context - a matching target would relate to both words, e.g., "coat"). Accordingly, CMT presents conflicting distractors of high, moderate, and low intensity to assess not only whether an interference is present but to what degree (i.e., are decisions in incongruent trials impaired only in the presence of strong competitors or also in the presence of weak or semantically unrelated competitors?).

Here, we present preliminary results on the pivotal features of the CMT, testing whether 1) the strength of the semantic link between stimulus and target affects decisions about contextually congruent and incongruent trials differently (i.e., bottom-up processing facilitates decisions on congruent but impairs decisions on incongruent trials), 2) whether the extent of impairment in contextually incongruent trials scales down with the strength of the semantic link between the stimulus and target (i.e., habitual activation spreads less onto weakly related and unrelated competitors), and 3) whether the cognitive costs associated with the resolution of irrelevant competitors involve distinct capacities than those engaged in contextually constrained or weakly cued semantic search.

2 Method

2.1 Participants

In total, 100 healthy, young individuals (59 females; mean age 22.7 ± 1.9 years) participated in the study. The sample comprised 82 right-handers, 10 left-handers, and eight mixed-handers, as indicated by the Edinburgh short-form handedness inventory (Veale, 2014). At the beginning of the test session, participants reported low levels of stress and fatigue (medians = "rather low") and high levels of concentration, motivation, and confidence (medians = "rather high"). All participants gave written consent and received financial rewards after completing the procedure.

2.2 Materials and procedure

The CMT included 75 items, each appearing in eight distinct conditions resulting from the manipulation of three factors: 1) the *presence of context* (i.e., the stimulus could appear with or without a context word), 2) *context congruency* (i.e., target word could be either congruent or incongruent with the context), and 3) *strength of semantic link* with the stimulus (i.e., there could be either strong, weak or no semantic link between the stimulus and target word – as operationalized by the logDice metric derived from the word-word collocation database of the Slovak National Corpus). Fig. 1 depicts example trials for each condition. Therefore, each item (i.e., stimulus) included eight target words, five appearing under context and three under no-context conditions, resulting in 600 trials. Across the conditions, we matched the target words in word length (M = 5.1, SD = 1.1), frequency (log: M = 4.5, SD = 0.6), and psycholinguistic properties of word concreteness (1 = abstract; 7 = concrete: M = 5.5, SD = 1.5), imageability (1 = hardly imageable; 7 = easily imageable: M = 5.6, SD = 1.3), emotional valence (1 = negative; 9 = positive: M = 5.3, SD = 1.1), and arousal (1 = calm; 9 = arousing: M = 4.6, SD = 1.0) (Scott et al., 2019).

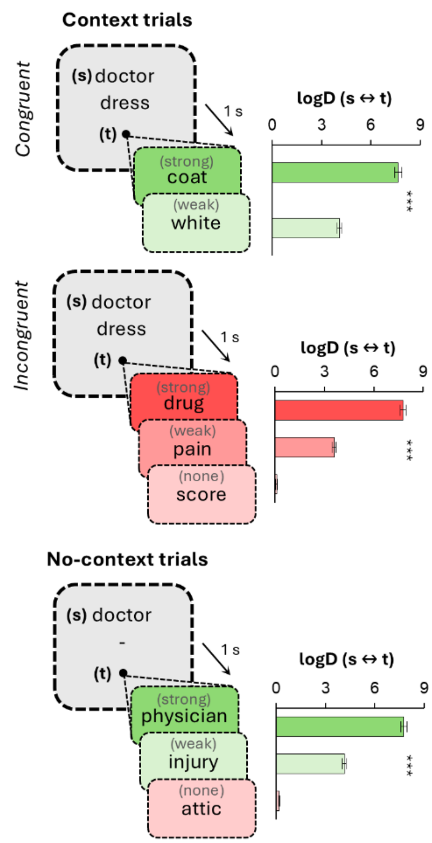

Fig. 1: Example trials of the CMT. On context trials, the stimulus (s) appeared with the context. On no-context trials only the stimulus appeared on the screen. After 1 second a target (t) appeared requiring the participant to respond whether it relates to the stimulus or not. Green and red color designate matching and mismatching targets, respectively. Color intensity designates strength of semantic link between the stimulus and target word (strong > weak > unlinked). Adjacent bar-plots show average logDice metric ± SE for strongly linked, weakly linked, and unlinked targets (75 targets for each condition). *** $p < .001$

The CMT was administered in individual laboratory sessions alongside other executive control tasks estimating working memory capacity, response inhibition, controlled associative memory retrieval and thought control. The task was programmed and controlled via the PsychoPy software (version 2024.2.1, Peirce et al., 2019). Participants completed CMT in three blocks (each including 25 items – 200 trials) administered in a counterbalanced manner. The conditions were inter-mixed within the task, and trials were presented in random order. Each trial began with a presentation of a stimulus word (with or without a context word). After one second, a target word appeared below the stimulus (and context). Participants were instructed to decide as fast as possible whether the target word semantically matches the stimulus (pressing the left arrow key) or not (pressing the right arrow key). On trials without a context word, the target could match the stimulus if *any* meaningful semantic link existed between the two. On trials with context, the target could match the stimulus *only if* satisfying the contextual demands (i.e., relates not only to the stimulus but also to the context word, see Fig. 1). The responses were measured for reaction time (RT) and accuracy.

2.3 Data processing and variables

Data were processed and analyzed in R (R Core Team, 2023). First, we checked the proportion of correct hits for each trial to identify poor items (to control for inflated error statistics). We adopted a strict rule to retain only items of which target words reached at least 70% overall accuracy (i.e., if the accuracy for one of the target words fell below this level, we removed all target words belonging to the stimulus in respective conditions to ensure that conditions remain homogenous in terms of stimulus and context words). Following this rule, we removed 23 items (41600 responses entered further processing). The conditions remained equal in target word length, frequency, and psycholinguistic properties ($p_{\text{Holm}} > .144$). Next, we treated RT data for erroneous responses (8.36% across all conditions) and outlier values (1.5 × IQR above the upper quartile in respective conditions, 7.04%) before applying 10% two-sided winsorization (by condition).

Finally, we averaged the RT data by condition for each participant. Then, we contrasted these averaged RTs to estimate individual costs (ΔRT) associated with the resolution of *high conceptual interference* (RT to strongly linked-incongruent – RT to strongly linked-congruent), *moderate conceptual interference* (RT to weakly linked-incongruent – RT to strongly linked-congruent), and *low conceptual interference* (RT to unlinked-incongruent – RT to strongly linked-congruent). Additional contrasts included 1) costs associated with *retrieving weak semantic links* (RT to weakly linked – RT to strongly linked matching target words in no-context trials, e.g., Badre & Wagner, 2006) and 2) costs associated with *constraining the semantic search by low contextual demands* (RT to strongly linked-congruent – RT to strongly linked target words in no-context trials) and *high contextual demands* (RT to weakly linked-congruent – RT to strongly linked target words in no-context trials).

2.4 Analyses

In the first set of analyses, we evaluated the effect of context congruency (congruent, incongruent) and semantic link (strong, weak) on RTs and errors using generalized linear mixed models (GLMM, gamma and binomial family of models with log and logit link functions, respectively, e.g., Lo & Andrews, 2015). Congruency and semantic link factors entered the models as fixed factors in interaction. Crucially, we specified maximal random effects structure, including random intercepts and slopes of all fixed effects and their interaction for participants and items (Barr et al., 2013). In practical terms, this approach allowed us to assess whether the context congruency and semantic link effects (plus their interaction) generalize over their variability within the current sample (i.e., the effects are not driven by 'few' individuals) and item set (i.e., the effects do not result from 'few' items for which they apply). We used the likelihood ratio test to assess the significance of fixed effects. In pairwise comparisons, we adjusted the p-values for four tests by Holm's method (strongly linked-congruent vs weakly linked-congruent, strongly linked-incongruent vs weakly linked-incongruent, strongly linked-incongruent vs strongly linked-congruent, and weakly linked-incongruent vs strongly linked-congruent). The RT GLMM included 17811 responses and error GLMM 20800 responses. Finally, we ran two additional GLMMs, one contrasting RTs in three context incongruent conditions against the RTs in strong congruent condition (i.e., formal assessment of demands on conflict resolution as a function of semantic link, strong > weak > unlinked) and second modelling RTs for matching target words as a function context (present, absent) and semantic link (strong, weak). Both models estimated maximal random effects structure.

In the second set of analyses, we conducted an exploratory factor analysis (EFA) on RT contrasts reflecting 1) costs from resolving high, moderate, and low conceptual conflict and 2) costs from retrieving weak semantic links and constraining semantic search by high and low contextual demands (i.e., six indicators). KMO and Bartlett's test of sphericity determined data sampling adequacy and suitability for EFA. To estimate the factor structure, we performed parallel analysis using the 'minres' method (Harman & Jones, 1966; Zegers & ten Berge, 1983) and retained only factors surpassing the 95th percentile of eigenvalues from 1000 simulated correlation matrices. Factors were rotated by the 'oblimin' method. Model fit was assesed by χ^2 test, TLI, RMSEA, and SRMR.

3 Results

3.1 Reaction time and error statistics

In line with our expectations, congruency (congruent, incongruent) and semantic link (strong, weak) factors yielded a robust interaction on RT, $\chi^2(1) = 38.24$, $p < .001$ (Fig. 2A left). This interaction showed that strong compared to the weak semantic link between the stimulus and target word slowed RTs in context-incongruent trials (ΔRT = +0.15s, $SE = 0.05$, $Z = 2.98$, $p_{\text{Holm}} = .003$), but facilitated RTs in context-congruent trials (ΔRT = -0.44s, $SE = 0.06$, $Z = -7.97$, $p_{\text{Holm}} < .001$). RTs on strong and weak incongruent trials were significantly longer than RTs on strong congruent trials (ΔRT = +0.50s and +0.35s, respectively, $Z > 6.09$, $p_{\text{Holm}} < .001$). Similarly, congruency and semantic link factors showed a reliable interaction on response errors, $\chi^2(1) = 281.09$, $p < .001$ (Fig. 2A right). Likewise, the interaction indicated that strong compared to the weak semantic link between the stimulus and target word led to a slightly higher error rates in context-incogruent trials (ΔError-rate = +2.5%, $SE = 0.8$, $Z = 3.11$, $p_{\text{Holm}} = .004$), but to lower error rates in context-congruent trials (ΔError-rate = -6.5%, $SE = 1.1$, $Z = -7.52$, $p_{\text{Holm}} < .001$). Only error-rates in strong but not weak ($p_{\text{Holm}} = .199$) incongruent trials were significantly higher than error rates in strong congruent trials (ΔError-rate = +3.5%, $SE = 0.9$, $Z = 4.31$, $p_{\text{Holm}} < .001$).

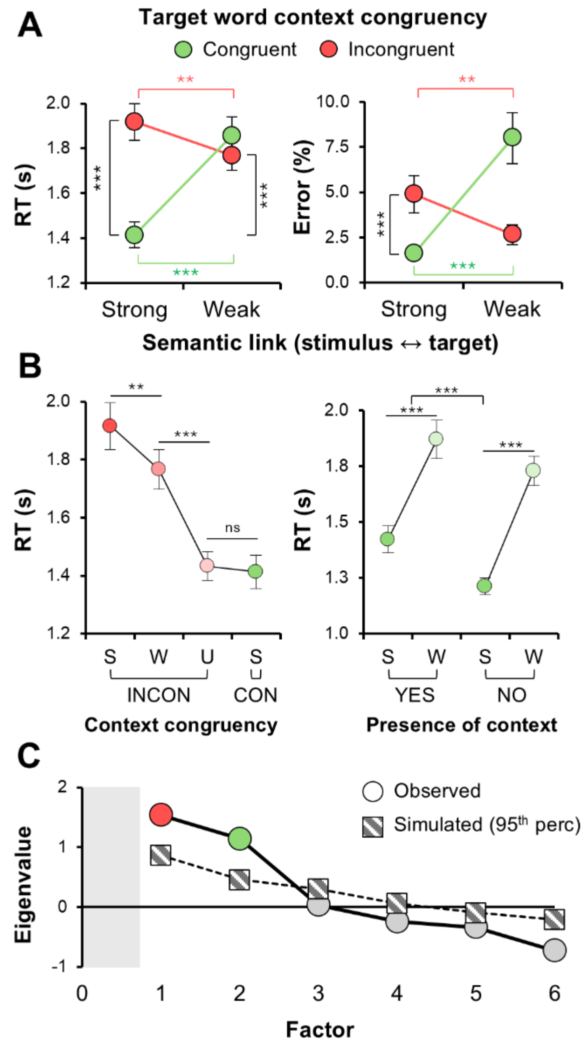

Fig. 2: A) RT (left) and errors (right) in CMT as a function of context congruency and semantic link factors. B) Left: RT on strongly linked (S), weakly linked (W) and semantically unlinked (U) trials in context congruent (CON) and incongruent (INCON) conditions. Right: RT to strongly and weakly linked targets in context and no-context trials. C) Scree plot of observed and simulated Eigenvalues from EFA on RT costs data. Red circle indicates factor capturing costs from resolving high, moderate, and low conceptual conflict, and green circle indicates factor capturing costs from retrieving weak semantic links and constraining search by low and high contextual demands. Error-bars show ± SE of the estimates. *** $p < .001$ ** $p < .01$ ^{ns} non-significant (Holm corrected).

The GLMM comparing RTs on incongruent trials against the RTs on strong congruent trials replicated the main effect of condition, $\chi^2(3) = 56.34$, $p < .001$, and additionally showed that RTs on semantically unlinked context-incongruent trials did not differ from RTs on strong context-congruent trials ($Z = 0.44$, $p_{\text{Holm}} = .663$), but differed significantly from RTs on strong and weak context-incongruent trials ($Z > 7.30$, $p_{\text{Holm}} < .001$, i.e., interference resolution costs decreased from strong to weak to no semantic link between the stimulus and target word, see Fig. 2B left).

Finally, the GLMM modelling RT as a function of context presence (yes, no) and semantic link (strong, weak) factors did not yield a significant interaction, $\chi^2(1) = 2.61$, $p = .106$. However, the main effects of context and semantic link were both significant, $\chi^2(1) > 13.09$, $p < .001$ (Fig. 2B right). Pairwise contrasts revealed that weak as compared to the strong semantic link substantially slowed RTs on context (ΔRT = +0.45s, $SE = 0.06$) as well as no-context trials (ΔRT = +0.52s, $SE = 0.06$), $Z > 7.07$, $p_{\text{Holm}} < .001$. RTs on strong and weak context trials were significantly longer than RTs on strong no-context trials (ΔRT = +0.21s and +0.66s, respectively, $Z > 3.92$, $p_{\text{Holm}} < .001$).

3.2 Exploratory factor analysis

RT costs data were found adequate for EFA (KMO = 0.70, Bartlett's test: $\chi^2 = 15.00$, $p < .001$). Parallel analysis suggested two factors for extraction (see Fig. 2C). Extracted factor structure showed an acceptable fit to the data, $\chi^2(4) = 6.87$, $p = .143$, TLI = .97, RMSEA = .08, SRMR = .015. The first factor explained 39.2% of the variance and saturated costs from resolving high (factor loading $\lambda = .93$), moderate ($\lambda = .91$), and low ($\lambda = .79$) conceptual conflict. The second factor explained 34.1% of the variance and saturated costs from retrieving weak semantic links ($\lambda = .53$) and constraining semantic search by low ($\lambda = .80$) and high ($\lambda = .99$) contextual demands. Factors showed small negative correlation, $r = -.115$.

4 Conclusions

In this study, we introduced a novel behavioral method for assessing the ability to resolve linguistic-conceptual conflict. First, the reaction time and error data from CMT confirmed that habitual semantic links play an opposing role in conflicting (i.e., context-incongruent) versus non-conflicting (i.e., context-congruent) conditions (Badre & Wagner, 2007; Macgregor et al., 2020; Ulrich et al., 2015). Specifically, while a strong conceptual link between the stimulus and target word accelerated the identification of a matching target, it impaired the resolution of a conflicting (or distracting) target. This dissociation aligns with the purported role of bottom-up (automatic) processes in the emergence of semantic interference (i.e., faster spread of semantic activation along habitual conceptual links promotes efficient retrieval of contextually relevant information but at the same time induces higher interference when irrelevant conceptual elements need to be resolved, Miller & Schwarz, 2021; Nedergaard et al., 2023; Nelson et al., 2008). Moreover, further analyses showed that the task design of CMT allows for parametric control of the intensity of conceptual conflict (i.e., RT costs on incongruent trials decreased as a function of semantic link strength, Fig. 2B left). Further support for this claim became apparent in EFA, which showed that RT costs associated with the resolution of contextually irrelevant information went beyond general costs stemming from imposing contextual demands or identifying less available semantic information. However, the results from the EFA may warrant further analyses in the future as RT costs derived for incongruent distractors versus congruent targets were contrasted against different baselines, which could artificially drive the observed two-factor structure. Nevertheless, when we subtracted the same RT (on strong context-congruent trials) in calculation of all RT costs, we still found the first factor reliably saturating only the costs from resolving interfering targets but not the costs related to identifying weak semantic links (i.e., the observed two factor structure did not result purely from ΔRT calculations). Finally, we note that the difference in resolution demands on weakly linked versus strongly linked incongruent trials may not seem considerable (i.e., ~ 150ms) despite presenting a ~ 30% decrease (against strong distractors). However, later iterations of the task may easily adjust this difference by considering multivariate and more robust metrics of semantic association in item construction and selection (e.g., combining human association norms and explicit ratings of relatedness with the data from distributional models of semantic memory or large language models, Kumar, 2021).

In summary, the CMT may offer novel means of assessing how unregulated executive control distorts the resolution of competing semantic information of varying intensity, which may be particularly relevant for addressing hypotheses regarding the sources of deficits in patients with language, memory, or thought impairment.

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