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Nuances of knowing: Brain potentials reveal implicit effects of domain knowledge on word processing in the absence of sentence-level knowledge

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Abstract

In previous work investigating the relationship between domain knowledge (of the fictional world of Harry Potter) and sentence comprehension, domain knowledge had a greater impact on electrical brain potentials to words which completed sentences about fictional "facts" participants reported they did not know compared to facts they did. This suggests that individuals use domain knowledge continuously to activate relevant/related concepts as they process sentences, even with only partial knowledge. As that study relied on subjective reports, it may have resulted in response bias related to an individual's overall domain knowledge. In the present study, we therefore asked participants with varying degrees of domain knowledge to complete sentences describing fictional "facts" as an objective measure of sentence-level knowledge. We then recorded EEG as the same individuals (re-)read the same sentences, including their appropriate final words, and sorted these according to their objective knowledge scores. Replicating and extending Troyer et al., domain knowledge immediately facilitated access to meaning for unknown words; greater domain knowledge was associated with reduced N400 amplitudes for unknown words. These findings constitute novel evidence for graded preactivation of conceptual knowledge (e.g., at the level of semantic features and/or relations) in the absence of lexical prediction. Knowledge also influenced post-N400 memory/integration processes for these same unknown words; greater domain knowledge was associated with enhanced late positive components (LPCs), suggesting that deeper encoding during language processing may be engendered when knowledgeable individuals encounter an apparent gap in their knowledge.

KEYWORDS

event-related brain potentials, individual differences, language comprehension, LPC, N400, semantic memory

1 | INTRODUCTION

Understanding language involves perceiving linguistic input, rapidly linking incoming words to existing knowledge, and attempting to create an intended message. To communicate, language users must share knowledge, yet no two language users share exactly the same knowledge and/or experiences. Indeed, conceptualizations even of everyday words differ across people (Martí et al., 2023), and this is reflected in neural responses to everyday language, images, and other sensory input (Armstrong et al., 2015). In the present study, we ask how variation in relevant domain knowledge impacts the moment-by-moment processing that gives rise to understanding written sentences, including activating and using word meaning in context.

Variation in domain knowledge is known to influence aspects of perception and cognition (reviewed in Ericsson et al., 2018). This research suggests that differences in individuals' degrees of knowledge of varied and diverse domains, including chess (de Groot, 1965; Simon & Chase, 1973), physics (Chi et al., 1981), and musical notation (Maturi & Sheridan, 2020), can impact how people link sensory input to their conceptual understanding and remember it for subsequent use. In chess, for example, experts organize meaningful/legal arrangements of chess pieces into “chunks,” mapping them onto their knowledge of templates/larger structures gleaned from experience playing chess (Gobet & Simon, 1996). Generally, greater domain knowledge benefits memory, although it can also increase false memories related to studied material (Castel et al., 2007).

In language research, the influence of domain knowledge has mostly been studied at the level of memory and comprehension of texts and, in some cases, at the speed of word-by-word reading. Knowledge availability can ease comprehension; for example, schematic knowledge (often manipulated with the presence/absence of a title) can allow readers to effectively read texts more quickly (Bransford & Johnson, 1972; Miller & Stine-Morrow, 1998; Wiley & Rayner, 2000). Domain-related knowledge can also benefit text comprehension, although “experts” may momentarily slow down when they integrate the text with their knowledge (Chin et al., 2015; Fincher-Kiefer, 1992; Miller, 2001, 2003; reviewed in Stine-Morrow & McCall, 2022).

In recent work, we have begun to investigate the electrophysiology of how domain knowledge impacts moment-by-moment written word processing during sentence comprehension using the narrative world of Harry Potter, a fictional fantasy microcosm with a rich array of people, places, objects, and relations among them. Our focus has been on event-related brain potentials (ERP), including N400s and, to some extent, post-N400 positivities, both of which have been linked to aspects of processing a word's meaning, albeit differently. In the present study, we use a novel paradigm to ask how domain knowledge influences the processing of words completing sentential “facts” which participants either knew or did not know, as measured objectively from their performance on a previous sentence completion task. We review relevant work examining the processes involved in real-time sentence comprehension using cognitive electrophysiology before presenting the current study.

1.1 | Sentence comprehension and long-term memory

Language comprehension is incremental (and often predictive) in nature, such that the interpretation of a sentence is updated with each incoming word and newly available information (DeLong et al., 2014; Kutas et al., 2011). Evidence for this claim comes in large part from studies using ERPs. N400 brain potentials, in particular, have been useful for understanding how individuals process words in sentences for their meaning (Federmeier, 2021; Kutas & Federmeier, 2000, 2011). N400 amplitudes are impacted by a host of factors related to processing a word's form and meaning as a function of both local (e.g., sentence) and global (e.g., language statistics) context. For example, N400 amplitudes increase as a function of a word's orthographic neighbors (Holcomb et al., 2002), even when the words occur within sentences (Laszlo & Federmeier, 2009). Likewise, when words are contextualized in meaningful sentences or multi-word strings, N400s are increasingly smaller (more positive) as semantic context accrues (Van Petten, 1993; Van Petten & Kutas, 1990), illustrating how sentence comprehension proceeds incrementally. N400 amplitudes are also reduced as a function of contextual predictability, often operationalized with cloze probability (the proportion of people who provide a given word when asked to continue a sentence frame; DeLong et al., 2005; Federmeier et al., 2007; Kutas & Hillyard, 1984). Indeed, facilitation (reduction in amplitude) of N400s occurs in graded fashion even for words with near (but non-) zero probability once those probabilities are log-transformed; this has been offered as evidence for probabilistic preactivation of not only individual words but also sub-word-level semantic features (Szewczyk & Federmeier, 2022).

A distinction can be made between understanding the meaning of a sentence and verifying whether or not it is true. For example, although Fischler et al. (1983) observed a large, N400-like negativity to the false completions of simple affirmative sentences like “A sparrow is a vehicle” compared to “A sparrow is a bird,” a different pattern was

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obtained for sentences in which negation was present (e.g., "A sparrow is not a vehicle" [true]; "A sparrow is not a bird" [false]). In this case, sentence-final words completing *true* sentences were associated with a larger N400-like negativity. The authors interpreted this finding as evidence that some aspects of sentential meaning are interpreted prior to verifying the trueness (or falseness) of the entire sentence. Similar results have been obtained for quantifiers like *most* and *few*, which may not immediately constrain incremental language comprehension without sufficient context (Urbach et al., 2015; Urbach & Kutas, 2010).

Findings like those of Fischler et al. (1983) are in line with work showing that incremental sentence interpretation reflects semantic memory organization: because the meaning of *sparrow* is closely related to that of *bird*, the semantic processing of *bird* is (quickly) facilitated, whereas that of *vehicle* is not. Indeed, access to information organized both taxonomically (Federmeier & Kutas, 1999) and thematically (Amsel et al., 2015; Bicknell et al., 2010; Ferretti et al., 2007; Matsuki et al., 2011; Metusalem et al., 2012; Paczynski & Kuperberg, 2012) can be quickly accessed and used during reading comprehension. Of course, the organization of long-term memory is not identical for all speakers of a given language, whose different life experiences presumably lead to different knowledge structures. For example, Hagoort and colleagues (2004) show that specific knowledge gleaned through world experiences (e.g., the fact that, in the Netherlands, trains are yellow but not white) could have a near-immediate impact on how individuals process the meaning of appropriate versus inappropriate words as they complete factual sentences ('*The Dutch trains are yellow/white/sour*.'). N400 brain potentials are reduced only for appropriate completions, like *yellow*, whereas both semantically inappropriate (*sour*) and pragmatically inappropriate (*white*) continuations elicit equally large N400s. Although not tested in the Hagoort et al. study, a logical assumption is that these pragmatic effects would obtain only for individuals with the requisite knowledge.

Many of the studies just described suggest that some aspects of meaning are computed at a level that does not match a full or complete interpretation of a sentence. To fully understand that "A sparrow is not a bird" is false, the brain may establish the meaning of the relationship between *sparrow* and *bird* prior to interpreting the full meaning of the sentence. A related perspective from cognitive electrophysiology comes from Federmeier (2021), who distinguishes between processes of *connecting* and *considering* during language comprehension. Federmeier views comprehension processes reflected by the N400 as largely implicit and involved in *connecting* meaningful multimodal perceptual input (e.g., words, images, and so on) with stores of knowledge. On this view, the temporal constancy of processes reflected in the amplitude of the N400 may aid in creating stable, temporary representations in the mind, which may then potentially be *considered* and used for further processing. Some examples of "considering" provided by Federmeier include inhibiting and/or revising linguistic predictions when they are not met or selecting from among multiple (or ambiguous) possible meanings of a word once it is possible to do so. Some of these cognitive operations are proposed to be reflected in post-N400 positive-going brain potentials. These may reflect a number of cognitive processes which are not obligatory in the same manner as those reflected in N400 amplitudes and which may be influenced by higher level discourse and task demands (Urbach et al., 2015).

In the current study, our primary questions concern how variation in domain knowledge might influence the relatively implicit meaning processing reflected in N400 potentials. In addition, we examined post-N400 late positivities, which in many cases may reflect memory and comprehension processes more likely to be under conscious (attentional) control, including active attempts to deeply encode information for subsequent use.

1.2 | Electrophysiological studies of domain knowledge and sentence comprehension

We recently examined how domain knowledge influences access to meaning during reading comprehension. In Troyer and Kutas (2018), participants read sentences, some about Harry Potter (HP) and some about general topics, which ended either in the best completion or another (unexpected) word designed to sound plausible; for example, '*Harry has a patronus. It takes the form of a stag [correct]/lizard [incorrect].*' HP knowledge influenced the N400 effects of contextual support for critical words in the HP sentences but not the control sentences. This relationship was driven by the neural response to the contextually supported completions, with reduced N400 amplitudes as a function of increasing domain knowledge. There were at least two possible explanations for this effect: individuals with greater knowledge might (strictly) have known a greater proportion of the fictional facts, leading to reduced N400s on average; or, instead, those with greater knowledge could have been accessing conceptual information beyond a single correct completion. This latter account would imply an added (real-time) advantage of domain knowledge beyond specific, trial-level knowledge; knowledgeable individuals might immediately engage rich mental models/schemas unavailable to those with less domain knowledge.

To adjudicate these possibilities, Troyer et al. (2019) focused on HP sentences with correct endings. Participants read fictional "facts" about the narrative world of HP, all of which ended in the best (correct) completion. After each sentence, participants were asked whether they had known that fact prior to the experiment. We therefore directly assessed whether high- and low-knowledge individuals processed the sentence-final words differently even when individuals made the same knowledge judgments in the moment. We determined that HP domain knowledge had an influence on N400 potential to completions judged as *unknown* but not those judged as *known*. We therefore hypothesized that domain knowledge mainly influences moment-by-moment access to word meaning when retrieval is possible but difficult. This pattern suggested that, even in the absence of "full" knowledge of the fictional facts, partial information (e.g., at the level of semantic features or related concepts) was available as a function of domain knowledge. In addition, we found that the effects of domain knowledge went beyond the N400 time period, with high-knowledge individuals showing larger late positivities compared to low-knowledge individuals and also only for trials judged as unknown.

However, given that trials were sorted based on participants' subjective judgments, we could not rule out the possibility that the observed group differences were due (at least in part) to differences in the decision-making criterion/threshold set by high- versus low-knowledge individuals (see Griffin et al., 2009, for underconfidence in judgments of text comprehension by experts). Therefore, for the present study, we designed a new paradigm in which we objectively measure trial-level knowledge of words completing fictional facts for each participant and each sentence immediately prior to ERP collection. During the ERP study, we also included a subjective measure of familiarity at the trial level to examine the impact of both domain knowledge and graded word-level knowledge on the processing of sentence endings that were not fully available to conscious report. In this way, we were able to examine the influence of domain knowledge on brain potentials to objectively known and unknown words at a relatively fine grain.

1.3 | The current study

Participants were asked to supply the final word for sentence pairs that described fictional facts about the HP world. Next, they read the same sentence pairs while their EEG was recorded, now with the correct final word included. On each trial, they also judged whether the actual completion matched their production during the sentence-completion task, followed by a judgment of their certainty (for known trials) or familiarity (for unknown trials). Finally, they completed behavioral tests designed to assess their knowledge of Harry Potter as well as other assessments of individual differences.

This design allowed us to assess knowledge in multiple ways, including participant-level knowledge (here referred to as "HP domain knowledge") and trial-level knowledge (i.e., the ability of a given participant to correctly complete a given item on a single trial). For example, a person might have seen at least a few HP movies once. They might know the names of a number of the major characters. They may know that Quidditch is the major sport in this world and that it is played on brooms, but they likely do not remember any specific matches or know the names of different positions on the team. They may know other specific facts about the HP world as well. However, they do not possess a rich, well-connected set of knowledge about HP. That is, they do not possess a rich knowledge structure that may facilitate memory for specific components of the HP world. By contrast, someone else may have read all of the books twice and may have seen every movie multiple times (perhaps even in order during a binge-watch of HP). They might know many individual facts about the HP world but may not remember all of them at any specific moment. They may also remember specific events in the HP world, their order to some extent, and cause–effect relationships among some of the events (e.g., what events led directly to others or were intertwined in the narrative). That is, they do possess a rich, multidimensional knowledge structure that could potentially facilitate access to and processing of specific facts about HP. By trial-level knowledge, we mean that a person has knowledge of a specific fact. HP domain knowledge refers to possessing rich, well-connected, multidimensional knowledge of the HP world.

In line with the literature (Troyer et al., 2019; see also Coronel & Federmeier, 2016; Fischler et al., 1983), we hypothesized that semantic access to known words compared to unknown words would be facilitated, as reflected by smaller N400 amplitudes. We further hypothesized that domain knowledge would additionally influence access to word meaning, specifically for unknown trials (those for which participants had not been able to produce the appropriate sentence completion). Judgments of certainty/familiarity also allowed us to sort trials with a finer grain, which was especially relevant for trials that had objectively been unknown during the sentence completion task. We expected that HP domain knowledge would primarily influence trials judged as familiar compared to unfamiliar, reflecting the availability of partial knowledge cued by domain knowledge.

In addition, post-N400, late positive complexes (LPCs) are often observed in language studies designed to elicit N400 effects and have been argued to reflect memory processes involved in encoding and recollection (reviewed in Van Petten & Luka, 2012; see also Rugg & Curran, 2007)

TABLE 1 Sample sentence pairs.

Sentence frame	Final word
There is one main sport in the wizarding community. It is known as	Quidditch
The character Peter Pettigrew changes his shape at times. He takes the form of a	rat
Harry eventually learns the truth about Sirius Black. Sirius is Harry's	godfather
Hermione owns a large, orange feline. Her pet is called	Crookshanks
To combat boggarts, wizards must think of something funny. They must use the spell	Riddikulus
Hogwarts students shop at Madam Malkin's. This is where they buy their	robes
Looking for Sirius, Harry and his classmates fly to the Ministry of Magic. They ride winged horses called	thestrals

and/or the integration of new information in an ongoing construction of a situation model at the message level (Brouwer et al., 2012). More broadly, they seem to reflect relatively "active," explicit processing compared to N400s, argued to reflect relatively more obligatory, implicit semantic processing (Federmeier, 2021). We expected that LPCs might be influenced by several factors. Deeper memory and/or integration processes might be present for unknown trials compared to known trials (since unknown trials provide a learning opportunity), leading to enhanced LPCs. LPCs might also reflect participants' certainty about their knowledge; relatively larger LPCs might be elicited by trials associated with intermediate levels of knowledge (i.e., trials judged as known/uncertain or unknown/familiar) compared to trials judged to be certain and/or completely unfamiliar, since these might not provide good opportunities for learning. Finally, higher knowledge individuals might exhibit relatively more positive-going LPCs overall, resulting from deeper encoding/recollection, and/or integration of the information with their existing knowledge. Alternately, domain knowledge might interact with trial-level knowledge, influencing LPCs for only unknown trials, as observed in Troyer et al. (2019).

2 | METHOD

2.1 | Participants

A total of 35 members of the University of Western Ontario community (mean age = 19, range = 17–28; 21 identified as female, 14 identified as male) took part in the study for partial course credit or cash. This number is similar to that in published studies investigating the impact of variability in Harry Potter domain knowledge on ERPs recorded during reading (e.g., Troyer et al., 2019). All participants provided informed consent reviewed by the Human Research Ethics Committee at the University of Western Ontario. For inquiries about data and code, please contact the first author.

2.2 | Materials

2.2.1 | Sentence materials

A total of 172 sentence pairs were used in the sentence completion task and the EEG reading experiment (Table 1). These ended in a critical word which correctly completed a statement about events/people/places/things from the stories of Harry Potter. A separate group of participants completed offline cloze norming (described in more detail in Troyer et al., 2019). The distribution of offline cloze probability for these items is plotted in Figure 1b.

2.2.2 | Measures of individual differences

Harry Potter knowledge quiz

Participants' knowledge about Harry Potter was estimated using their scores on a trivia-style quiz containing 10 multiple-choice questions (4 choices per question). HP quiz score (henceforth, "HP knowledge") was the correct number of answers out of 10 (z-transformed in all regression analyses). For visualization purposes only, we plot high- versus low-HP knowledge groups according to a median split based on this Harry Potter knowledge score.

Harry Potter self-report

Participants completed a questionnaire about their experience with the Harry Potter books, movies, audiobooks, and other Harry Potter-related activities (details in Troyer & Kutas, 2018). Scores were determined by summing the total number of times they had read each book, seen each movie, and so on.

General knowledge quiz

Participants' knowledge about general topics including popular culture, science, geography, politics, religion,

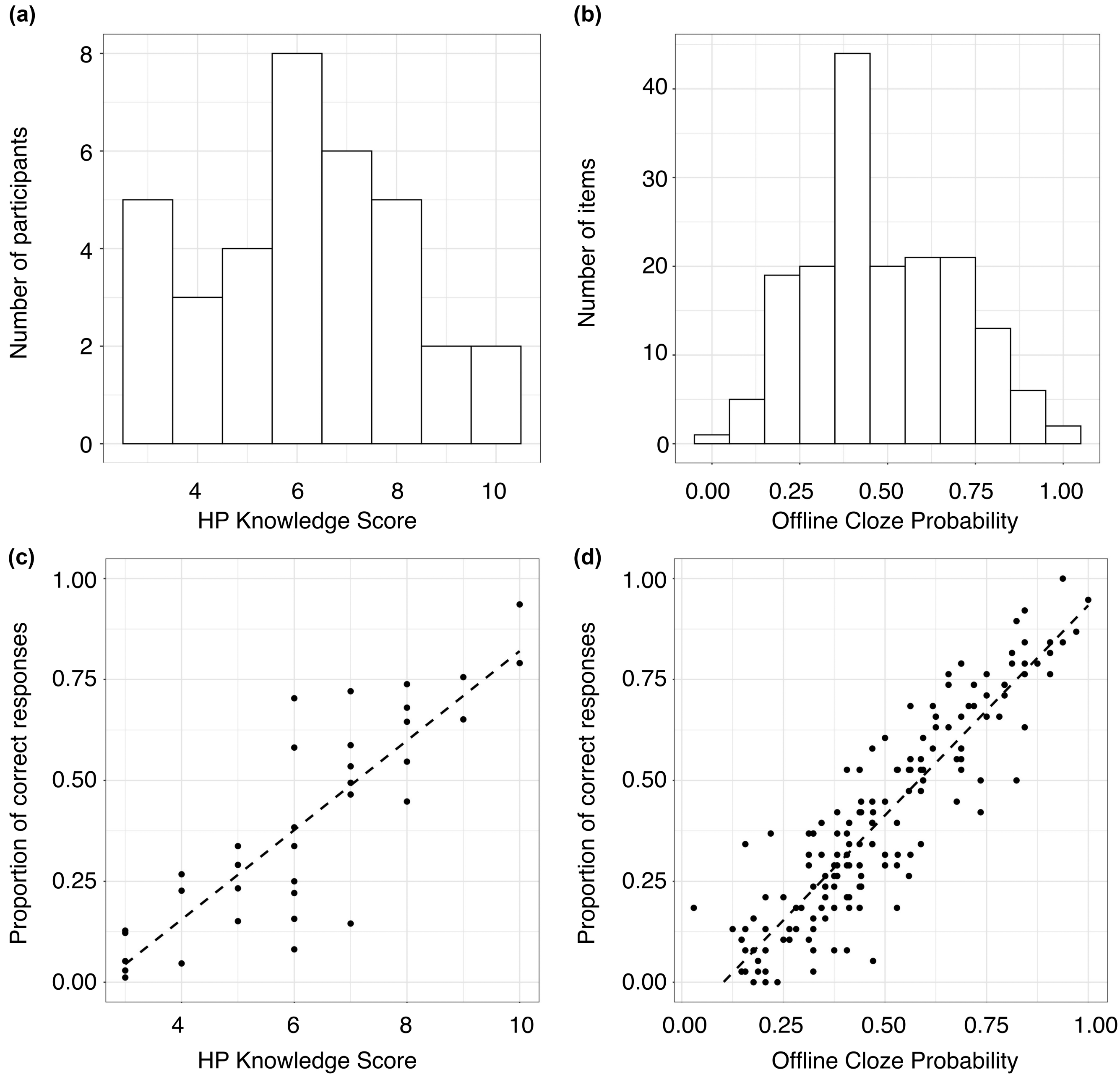

FIGURE 1 (a) Distribution of HP knowledge scores across participants. (b) Distribution of offline cloze probability across items. (c) Each participant's HP knowledge score plotted against the proportion of trials for which they produced the correct ending during the sentence-production task. The two are correlated at $r = .85$, $p < .0001$. (d) Offline cloze probability for each item plotted against the proportion of participants who correctly produced that word during the sentence-completion task. The two are correlated at $r = .90$, $p < .0001$.

literature, and art was estimated using a 30-question, multiple-choice general knowledge quiz, adapted from our original version (GKQ; Troyer & Kutas, 2018) for use in Canada.

Measures of print exposure and reading/media habits
Print exposure was measured using adaptations of the Author (ART) and Magazine (MRT) recognition tests and the Media and Research Habits (MRH) questionnaire (Stanovich & West, 1989).

2.3 | Procedures

2.3.1 | Ordering of tasks

After providing informed consent, participants completed the sentence completion task. They completed the ART/MRT during EEG set-up. They then completed the EEG experiment. After the EEG experiment, they completed the MRH. Finally, they completed a set of computerized individualized difference measures in the following order:

Harry Potter self-report, Harry Potter knowledge quiz, and general knowledge quiz. A general schematic of the experimental procedures can be found in Figure S1.

2.3.2 | Sentence completion task

In a computerized task, participants were asked to provide the best completion (according to the stories of Harry Potter) for pairs of sentences about the fictional world of Harry Potter, the final word of which was missing. They were told not to use external sources and that they were not expected to know the ending to every sentence; however, they were encouraged to guess the correct word and/or go with what came to mind for trials which they did not know.

2.3.3 | EEG experiment

Participants were given instructions to remain relaxed and still to minimize muscle artifacts. They were told they would be reading the same two-sentence stories about Harry Potter that they had read during the previous sentence completion task, except that now the stories would be completed with the correct word. They were then instructed to make a series of decisions about the sentences. First, they were asked to indicate whether the final word matched what they had produced (written) during the sentence completion task. If they answered yes, they were instructed to judge their certainty ("Yes" for certain and "No" for not certain). If they answered no, they were instructed to judge whether, after having read the correct word, it seemed familiar. In other words, they should answer "Yes" if the word now seemed familiar (as though they could now remember it) and "No" if they felt they had never known that particular Harry Potter "fact."

During the EEG experiment, participants sat approximately 100 cm in front of a flat-panel monitor. The background of the screen was black, and words were presented in white type. Each trial began with a blank screen for two seconds. Then, the first sentence of each pair appeared on the screen until the participant pressed a button to advance to the next sentence. After their button press, a crosshair appeared in the center of the screen for a duration which varied randomly between 900 and 1100 ms. Participants were instructed to focus on the crosshair and not to move their eyes or blink while it was on the screen. The second sentence was then presented one word at a time, right above the crosshair. Each word was presented for 200 ms with an interstimulus interval of 300 ms (SOA of 500 ms). After the sentence-final word disappeared, the crosshair stayed on the screen for a duration that randomly varied between 900 and 1100 ms. A blank screen then appeared for one second, followed by the display of the first question: "Match?" Below this question, the two responses ("Yes" and "No") were displayed. After their response, the follow-up question was displayed. If participants had answered "Yes," they saw the question "Certain?" along with the possible responses ("Yes" and "No"). If they had answered "No" to the first question, they instead saw the question "Familiar now?" along with the possible responses ("Yes" and "No"). In all cases, participants were instructed to respond using a keyboard: "f" for "Yes" and "j" for "No."

2.4 | EEG recording

The electroencephalogram (EEG) was recorded from 32 Ag-AgCl active electrodes using a BioSemi Active-Two system with a DC amplifier. Electrodes were arranged according to the standard 10–20 system and were mounted in an elastic electrode cap. Electrodes were also placed lateral to the outer canthus of each eye (for use in monitoring eye movements), under each eye (for use in monitoring blinks), and behind the ears on each mastoid. During recording, all electrodes were referenced online using a combined ground/reference (CMS/DRL) circuit. The EEG was digitally sampled at 512 Hz. DC offsets were maintained at ±20 mV.

2.5 | Data analysis

2.5.1 | Behavior

For the sentence completion task, participants' typed responses were manually corrected for spelling. We report Pearson's r for correlations between HP knowledge scores and the proportion of correct responses on the sentence completion task; the proportion of each response type during the EEG experiment; and the other individual difference variables. We report descriptive statistics for accuracy on the sentence completion task and the proportion of each response type during the EEG experiment.

2.5.2 | EEG

2.5.2.1 | *Filtering, artifact correction, and epoching*

All electrodes were re-referenced offline to an averaged mastoid reference. In addition, the left horizontal eye channel was re-referenced offline to the right horizontal eye channel to create a bipolar channel to monitor horizontal eye movements. Data were digitally filtered using a bandpass of 0.1 to 30 Hz. We extracted single-trial epochs of EEG data from the continuous recordings from 500 ms prior to the onset of a critical word until 1000 ms post-critical word. Even though participants had been instructed not to blink during the second sentence, 16% of trials were contaminated with an eyeblink during this 1500-ms window. The data were then subjected to an Independent Component Analysis (ICA) to identify blink components using EEGLab's AMICA routine in Matlab. We used the identified blink components to correct only the trials that contained blinks. Applying this procedure resulted in an average loss of only 2% of trials per participant due to blinks. We then removed trials contaminated by other artifacts, including movements, skin potentials, excessive muscle activity, and any remaining blink activity, resulting in a loss of 7% of data due to any artifact overall. For each electrode, a baseline computed by averaging potentials from 500 ms before the word to the start of the word was subtracted from the waveform prior to analysis.

2.5.2.2 | *Extraction of time windows*

For statistical analyses, we averaged data from individual trials across two time windows: (1) 250–500 ms after critical word onset, corresponding to the typical peak of the N400 brain potential and (2) 600–900 ms after word onset, during which LPCs often appear. For both time windows, we focused on a centro-parietal region of interest (ROI) where N400 and LPC effects are typically most prominent, averaging across 8 electrodes: FC1, FC2, C3, Cz, C4, CP1, CP2, and Pz.

2.5.2.3 | *Statistical analysis*

As the experiment was designed to examine differences between participants in their domain knowledge and knowledge at the single-trial (i.e., sentence) level, there were vastly different numbers of trials per cell (known, unknown) across participants. We therefore used hierarchical mixed-effects linear regression, which allows for different counts per cell (Baayen et al., 2008), to model single-trial data extracted from the N400 and LPC time windows. Models included random intercepts for item and participant and were implemented using lme4 (1.1–23; Bates et al., 2015) and lmerTest (3.1–3; Kuznetsova et al., 2017). For statistical inferences about covariates of interest, we performed model comparisons and reported chi-square statistics on nested models. Categorical predictors were deviance-coded (e.g., known trials = 1 and unknown trials = −1), and continuous predictors were z-transformed so that a value of ±1 reflected a single standard deviation above or below the mean (at 0).

3 | RESULTS

3.1 | Behavioral data

3.1.1 | Individual differences in tasks

As in our prior work (Troyer & Kutas, 2018, 2020; Troyer et al., 2019, 2022), there was substantial variability in HP knowledge across individuals (Figure 1a; Table 2). Table 2 reports descriptive statistics for participants' scores on the HP trivia quiz and other measures of individual differences. Intercorrelations among individual difference measures are provided in Table 3. Of particular relevance, both HP measures (HP Quiz and HP Self Score) were moderately correlated with measures of reading experience (particularly from the Media and Reading Habits questionnaire) and general knowledge, as we have observed in previous studies.

3.1.2 | Sentence completion task

Participants supplied the correct sentence completion (or spelling-corrected correct completion) an average of 40% of the time [CI: 31%, 48%]. As anticipated, the proportion of correct trials correlated strongly with HP knowledge scores, $r = .85$, $p < .0001$ (Figure 1c). Item-wise offline cloze probability was also strongly correlated with the proportion of participants who knew each item, $r = .90$, $p < .0001$ (Figure 1d). As expected, this reflects that more predictable sentence endings (as estimated by cloze probability) were known by more participants.

3.1.3 | Knowledge judgments during the ERP experiment

During the ERP task, participants correctly responded to whether the correct given completion matched their actual typed response from the previous sentence completion task on 95% (95% CI = [94%, 96%]) of trials. For quantifying responses to the follow-up questions, we examine only these correctly identified trials, i.e., trials that participants correctly judged they had known and those that they correctly judged they had not known.

For known trials, participants were generally certain they had known the trials: they responded with "Yes" (known) + "Yes" (certain) on 39% of all trials and "Yes" (known) + "No" (uncertain) on 2% of trials. For unknown trials, participants responded with "No" (unknown) + "Yes" (the trial now seems familiar) on 31% of trials and "No" (unknown) + "No" (not familiar) on 28% of trials. A visualization of response type by HP knowledge score is displayed in Figure 2.

TABLE 2 Mean, standard deviation, and range are provided for behavioral measures of individual differences.

	All participants			High HP knowledge subgroup			Low HP knowledge subgroup		
	Mean	95% CI	Range	Mean	95% CI	Range	Mean	95% CI	Range
HP Quiz	6.14	[5.46, 6.83]	[3, 10]	8.00	[7.41, 8.59]	[7, 10]	3.92	[3.34, 4.49]	[3, 5]
# of HP Books	1.24	[0.76, 1.71]	[0, 4+]	2.27	[1.60, 2.94]	[0.71, 4+]	0.12	[−0.07, 0.31]	[0, 1]
HP Self Score	33.57	[25.58, 41.56]	[0, 71]	51.00	[41.89, 60.11]	[23, 68]	10.42	[3.11, 17.72]	[0, 32]
ART	0.13	[0.10, 0.17]	[−0.03, 0.60]	0.14	[0.11, 0.17]	[−0.08, 0.28]	0.13	[0.03, 0.23]	[−0.03, 0.60]
MRT	0.13	[0.10, 017]	[−.08, 0.38]	0.15	[0.08, 0.22]	[−0.07, 0.38]	0.14	[0.09, 0.19]	[0.05, 0.30]
# Authors Listed	1.89	[1.41, 2.36]	[0, 5]	2.13	[1.51, 2.76]	[0, 4]	1.50	[0.47, 2.53]	[0, 4]
MRH total	5.89	[4.97, 6.80]	[0, 12]	7.07	[5.51, 8.63]	[4, 12]	4.25	[2.67, 5.83]	[0, 8]
GKQ	17.82	[16.61, 19.04]	[10, 26]	18.93	[17.35, 20.52]	[15, 26]	15.91	[13.61, 18.21]	[10, 22]
Reading Experience	0.02	[−0.21, 0.25]	[−1.23, 1.98]	0.23	[−0.08, 0.53]	[−0.75, 1.23]	−0.19	[−0.72, 0.34]	[−1.23, 1.98]

TABLE 3 Intercorrelations (Pearson's *r*) among behavioral measures of individual differences. *r* values above .33 are significant at *a* = .05; *r* values above .47 are significant at *a* = .01.

	1	2	3	4	5	6	7	8
1 HP Quiz	1	0.81	0.19	0.12	0.55	0.25	0.39	0.42
2 HP Self Score	-	1	0.17	−0.05	0.48	0.34	0.29	0.35
3 ART	-	-	1	0.42	0.22	0.25	0.40	0.72
4 MRT	-	-	-	1	0.04	0.19	0.56	0.63
5 MRH	-	-	-	-	1	0.38	−0.03	0.62
6 # Authors Listed	-	-	-	-	-	1	0.02	0.68
7 GKQ	-	-	-	-	-	-	1	0.36
8 Reading Experience	-	-	-	-	-	-	-	1

Abbreviations: ART, author recognition test; GKQ, general knowledge quiz; MRH, media and reading habits; MRT, magazine recognition test.

3.2 | ERP data

Figure 3 displays trial-averaged ERPs across 32 scalp electrodes from 500 ms before the critical word onset to 1000 ms post-critical word, with separate waveforms computed for known and unknown trials. Across most electrodes, ERPs to critical words for both trial types are characterized by two early sensory components (N1 and P2). Following the P2, there is a wave during the N400 time period that is mostly positive-going for known trials and relatively negative-going for unknown trials. Following this, a posterior positivity is present, which is enhanced for unknown trials relative to known trials.

3.2.1 | N400 time period (250–500 ms)

Known versus unknown trials

We first examined the influence of trial-level knowledge on N400 effects. A linear mixed-effects model with trial-level knowledge as a predictor (Table S1) was compared to a nested model with only an intercept term as a predictor; the complex model was preferred ($\chi^2(1) = 37.516$, $p < .0001$). This pattern confirmed our hypothesis (in line with previous research) that known trials were accompanied by reduced N400 amplitudes compared to unknown trials.

Influence of HP knowledge on known versus unknown trials

We examined whether HP knowledge interacted with trial-level knowledge (Figure 4). Results from a linear mixed-effects model crossing trial-level knowledge (known and unknown) and HP knowledge as fixed effects are presented in Table S2. Both trial-level knowledge and the interaction of trial-level knowledge and HP knowledge were significant predictors. We compared this model to a simpler model which did not include the interaction term (HP knowledge X trial-level knowledge), finding that the more complex model was preferred ($\chi^2(1) = 51.92$, $p < .0001$). This suggests that HP knowledge modulated the effect of trial-level knowledge and explained N400

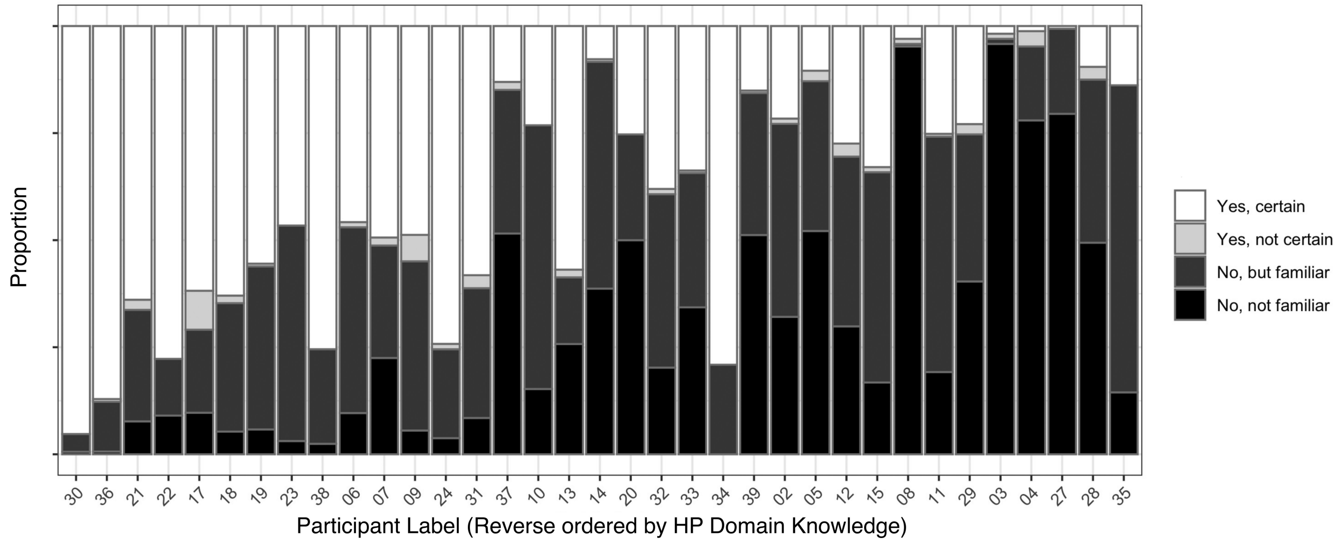

FIGURE 2 Proportion of trials of each response type (during the ERP study) plotted by participant, ranked by HP knowledge score (highest on left, lowest on right).

amplitudes above and beyond participants' trial-level knowledge of each fictional "fact."

We then directly tested the prediction that HP knowledge would have its greatest influence on N400 amplitudes during unknown trials (and little to no influence on known trials). To do so, we examined the known and unknown trials separately. For known responses, a model incorporating HP knowledge was not preferred over an intercept-only model ($\chi^2(1)=1.82$, $p=.178$; Table S3a). By contrast, for unknown responses, a model incorporating HP knowledge was preferred ($\chi^2(1)=7.46$, $p=.006$; Table S3b). These analyses provide direct evidence that HP knowledge influenced neural activity during the N400 time period for trials in which participants had not known the correct completion during the sentence completion task. Although the analysis for the known trials suggested no significant role of domain knowledge on known responses, a visual inspection of the high- versus low-knowledge groups (Figure 4; left panel) suggests this may be a result of low-knowledge-individuals contributing relatively few known trials to the analysis (as they know less), leading to relatively high variability.[1]

[1]As a reminder, statistics were computed over the entire sample, whereas for visualization purposes, we use a median split to determine groups with relatively high versus low HP knowledge. See Figure S2 for scatter plots of HP knowledge and ERP amplitudes (N400 and LPC time windows, respectively), which indicate the number of trials for each response type per participant. Inspection of mean amplitude at the participant level for the known trials suggests that a single high-knowledge individual who contributed a high number of trials may be obfuscating a more general trend for high-knowledge individuals to exhibit relatively less positive-going ERPs in both the N400 and LPC time periods.

We asked whether the observed influence of HP knowledge on N400s might be better explained by other existing individual differences among participants. We therefore examined a linear mixed-effects model predicting N400 amplitude from trial-level knowledge, HP knowledge, general knowledge, and reading experience, along with the interaction of each of the individual-difference variables with trial-level knowledge (Table 4). In this model, both trial-level knowledge and the interaction between trial-level knowledge and HP knowledge were significant predictors, suggesting that even when other individual differences are included, HP knowledge still modulates the influence of trial-level knowledge on N400 brain potentials. In addition, the interaction between trial-level knowledge and reading experience was a significant predictor, suggesting that factors relating to literacy also modulated the influence of trial-level knowledge on N400 amplitudes. To examine these effects further, we compared this full model with a nested model incorporating HP knowledge, trial-level knowledge, and their interaction as predictors (described above), finding that the more complex model explained greater variance ($\chi^2(4)=11.89$, $p=.018$). Thus, individual differences beyond HP knowledge (in this case, factors related to literacy) modulated the influence of single-trial-level knowledge on N400s; however, HP knowledge had a greater influence than any of these additional individual differences.

Unknown-familiar versus unknown-unfamiliar trials

We examined whether there were overall differences among unfamiliar trials according to participants' subsequent familiarity judgments during the ERP study (Figure 5). We further restricted these analyses to trials

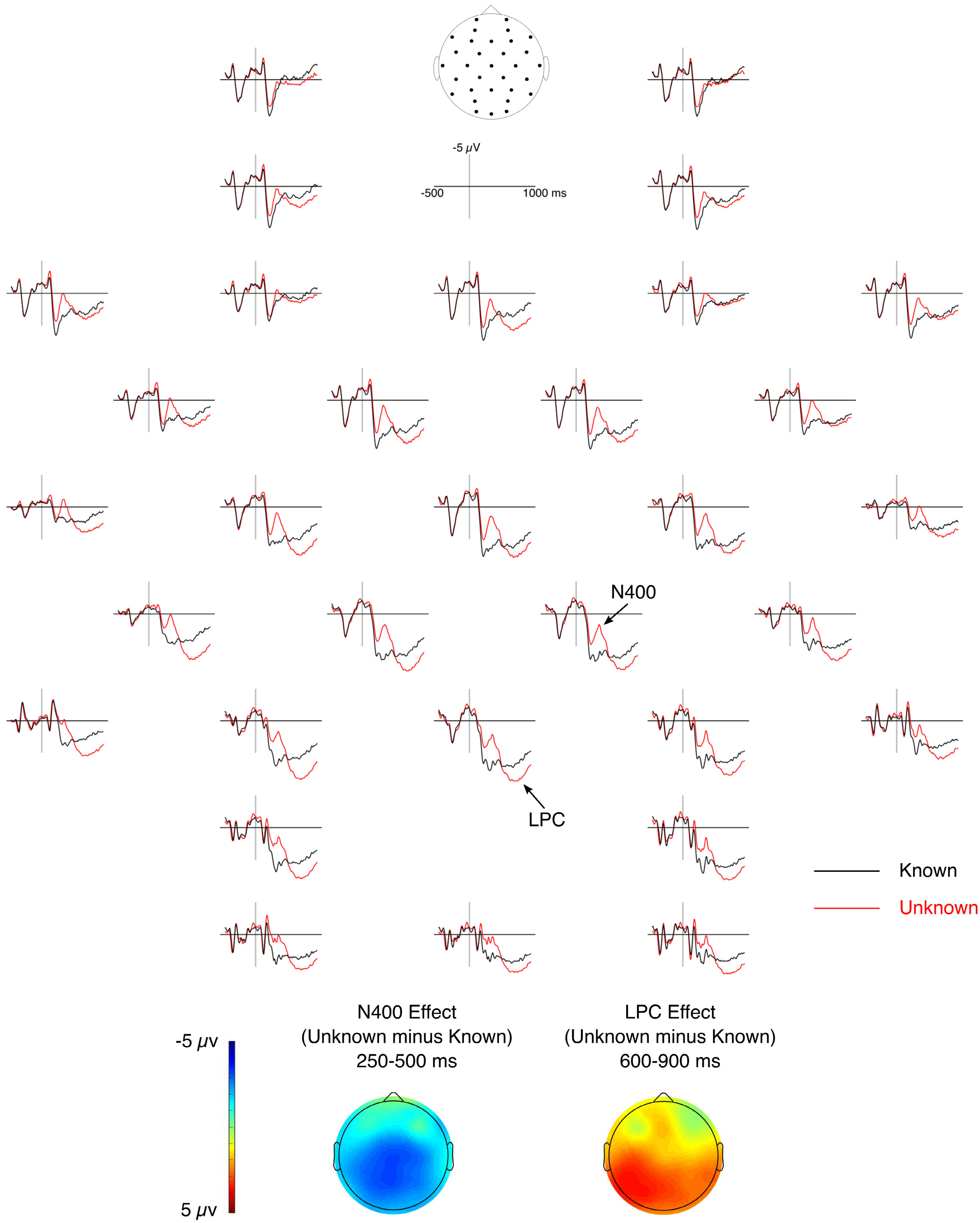

FIGURE 3 Grand average ERPs across all single trials to critical words are plotted across the whole head. Electrode locations are shown on the head in the center.

(correctly) judged as unknown during the ERP study. We compared a linear mixed-effects model with familiarity (familiar versus unfamiliar) as a predictor (Table S4) to a nested model incorporating only an intercept term, finding that the more complex model was preferred ($\chi^2(1) = 15.793$, $p \leq .0001$). As predicted, N400 amplitudes

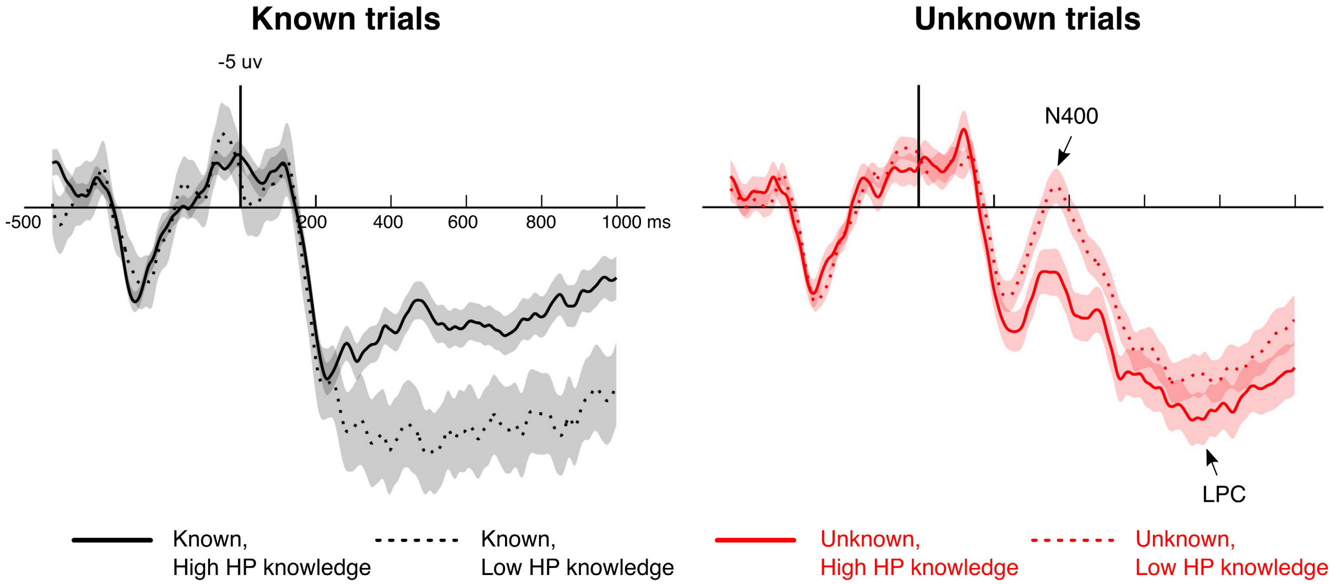

FIGURE 4 Trial-averaged ERPs to critical words across a centro-parietal ROI (see text) are plotted by HP knowledge group (high, low) and trial knowledge. The shaded region indicates 95% confidence intervals computed over single trials. For known trials, the effect of HP knowledge on the N400 and LPC time periods was not significant, despite the visually obvious difference shown here (see text for discussion). For unknown trials, HP knowledge had a significant impact on amplitudes in both the N400 and LPC time periods.

TABLE 4 Statistics for fixed-effects predictors of mean ERP amplitude in the N400 time period in an analysis of HP knowledge and other individual-differences measures.

	Estimate	SE	DF	t	Pr(> |t|)
Intercept	5.289	0.656	34.101	8.057	.0000
Trial-level knowledge	−1.459	0.205	2403.033	−7.123	.0001
HP knowledge	−0.208	0.743	30.789	−0.279	.7818
Reading experience	2.118	1.102	30.738	1.921	.0640
General knowledge	−0.233	0.718	30.105	−0.325	.7476
Trial-level knowledge: HP knowledge	1.359	0.233	4911.897	5.841	.0000
Trial-level knowledge: Reading experience	0.887	0.327	5040.286	2.710	.0068
Trial-level knowledge: General knowledge	−0.214	0.219	4643.484	−0.980	.3270

were reduced in cases where individuals judged previously incorrect items as seeming familiar compared to those judged as unfamiliar.

Influence of HP knowledge on unknown-familiar versus unknown-unfamiliar trials

We asked whether HP knowledge might have an influence primarily on the trials which were unknown but subsequently judged as familiar (unknown-familiar) compared to those which were unknown and later judged as not familiar (unknown-unfamiliar) (Figure 6).

We compared a linear mixed-effects model incorporating HP knowledge and familiarity levels (along with their interaction; Table S5) to a nested model incorporating only additive effects of HP knowledge and familiarity levels, finding that the simpler model was preferred ($\chi^2(1) = 0.026$, $p = .87$). Given that we had specifically hypothesized that HP knowledge would have its strongest influence on familiar trials, we performed planned follow-up nested model comparisons using models fit to subsets of the data according to familiarity level (familiar, unfamiliar). The more complex models incorporated HP knowledge as a predictor; these were compared to models with only an intercept term. When the familiar trials were considered alone, the complex model was preferred ($\chi^2(1) = 4.441$, $p = .035$), indicating that HP knowledge had an influence on N400s. In contrast, when unfamiliar trials

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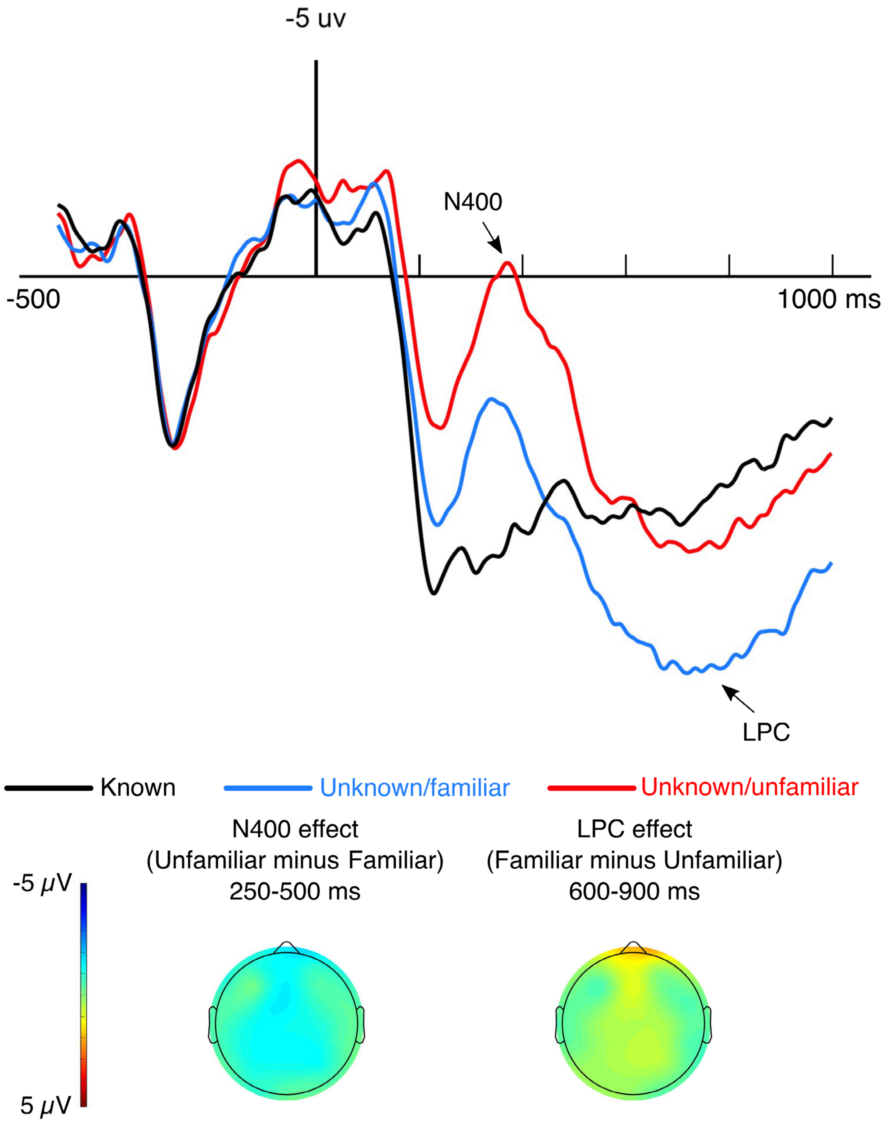

FIGURE 5 Trial-averaged ERPs to critical words across a centro-parietal ROI (see text) are plotted by trial knowledge and familiarity.

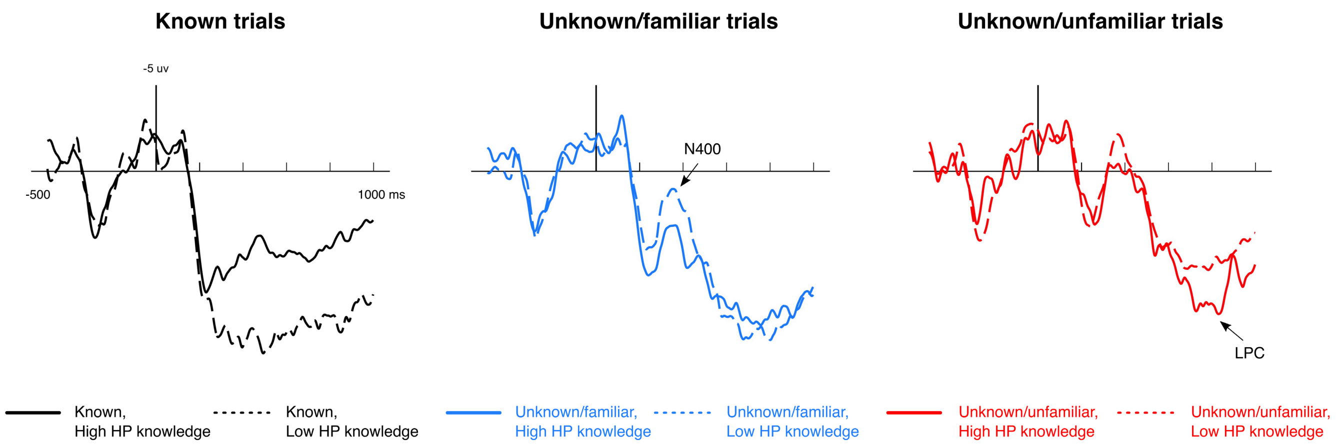

FIGURE 6 Trial-averaged ERPs to critical words for a centro-parietal ROI (see text) are plotted by HP knowledge group (high, low) and trial knowledge (known on left, unknown/familiar in center, known/unfamiliar on right). See Figure S2 for by-participant scatter plots showing N400 and LPC amplitudes as a function of each participant's HP knowledge.

were considered alone, the simpler model was preferred ($\chi^2(1) = 2.075$, $p = .150$). However, given the lack of interaction between HP knowledge and familiarity level, we conclude that it is likely that HP knowledge had at least some influence across the board for unknown trials, regardless of familiarity.

Summary

In sum, we replicated previous findings that N400s were influenced by HP knowledge primarily for unknown (compared to known) trials. Notably, for the first time, we have shown that this relationship obtained when the trial-level knowledge was measured objectively. Moreover, we extended these findings to show that the effect of HP knowledge was most apparent for trials later judged as familiar. These findings suggest that domain knowledge may have its largest influence when retrieval is difficult but possible (at least partially).

3.2.2 | LPC time period (600–900 ms)

Known versus unknown trials

We first examined the influence of known compared to unknown trials on LPCs. We compared a linear mixed-effects model incorporating trial-level knowledge as a predictor (Table S6) to a nested model incorporating only an intercept term, finding that the more complex model was preferred ($\chi^2(1) = 39.963$, $p \leq .0001$). Late positivities were enhanced for unknown trials compared to known trials (Figure 3).

Influence of HP knowledge on known versus unknown trials

Results from a linear mixed-effects model crossing trial-level knowledge (known, unknown) and HP knowledge as fixed effects are presented in Table S7. We compared this model to a simpler model that did not include the interaction term, finding that the more complex model was preferred ($\chi^2(1) = 23.543$, $p \leq .0001$). This suggests that HP knowledge modulated the influence of trial-level knowledge on LPC amplitudes; in other words, HP knowledge had an influence above and beyond participants' trial-level knowledge of each fictional "fact."

We investigated this interaction more closely by looking at known and unknown trials separately (Table S8). For known responses, a model incorporating HP knowledge was not preferred over the simpler intercept-only model ($\chi^2(1) = 0.518$, $p = .472$), suggesting no explanatory power of HP knowledge for known trials. For unknown responses, the more complex model incorporating HP knowledge was preferred ($\chi^2(1) = 6.048$, $p < .05$), suggesting that domain knowledge influenced unknown trials during the late positivity time period (Figure 4).

We asked whether the observed influence of HP knowledge on LPC amplitudes might be better explained by other differences among participants. We therefore used a mixed-effects linear regression model to predict late positive amplitudes using three individual-difference variables (HP knowledge, general knowledge, and reading experience) as well as trial-level knowledge and its interaction with each of the individual-difference variables (Table 5). Compared to a nested model including HP knowledge, trial-level knowledge, and their interaction, the simpler model was preferred ($\chi^2(4) = 6.353$, $p = .174$), suggesting that other individual differences did not have further explanatory power for late positive potentials.

Unknown-familiar versus unknown-unfamiliar trials

When examining trials that were unknown, we restricted these analyses to trials that were also later judged as unknown (followed by a familiarity judgment) during the ERP experiment. We had hypothesized that familiar trials might lead to relatively greater late positivities compared to unfamiliar trials. We therefore compared a linear mixed-effects model incorporating familiarity as a predictor (Table S9) to a nested model with only an intercept term, finding that the complex model was preferred ($\chi^2(1) = 15.793$, $p < .0001$). As expected, late positivities were enhanced for familiar unknown trials compared to unfamiliar unknown trials (Figure 5; whole-head plot shown in Figure S3). One difficulty in interpreting this result is that the directionality of the familiarity effect (familiar versus unfamiliar) on LPC amplitudes is in the same direction as the N400 effect, leading to the possibility that ERPs are not returning to baseline prior to the LPC time period (i.e., there may be component overlap). We recognize this difficulty in interpretation and cautiously suggest that the effects of familiarity at least persist into the LPC time period, possibly riding atop an LPC potential which is present for both the unknown-familiar and unknown-unfamiliar trials. We consider this further in the Discussion.

Influence of HP knowledge on unknown-familiar and unknown-unfamiliar trials

We were also interested in whether HP knowledge might have an influence primarily on LPCs for trials which were unknown but subsequently judged as familiar (unknown-familiar) compared to those which were unknown but later judged as not familiar (unknown-unfamiliar). A model incorporating HP knowledge and familiarity levels (along with their interaction) (Table S10) was compared to a model incorporating only additive effects of HP knowledge and familiarity; the simpler model was preferred ($\chi^2(1) = 2.353$, $p = .125$). However, there was a near-significant difference between the models, and visual inspection (Figure 6)

TABLE 5 Statistics for fixed-effects predictors of mean ERP amplitude in the LPC time period in an analysis of HP knowledge and other individual-differences measures.

	Estimate	SE	DF	t	Pr(> |t|)
Intercept	6.998	0.666	34.096	10.509	.0000
Trial-level knowledge	1.194	0.243	1868.537	4.907	.0000
HP knowledge	−0.376	0.756	31.170	−0.498	.6222
Reading experience	2.174	1.121	31.150	1.939	.0616
General knowledge	−0.019	0.729	30.231	−0.026	.9796
Trial-level knowledge: HP knowledge	1.111	0.282	4506.939	3.933	.0000
Trial-level knowledge: Reading experience	0.458	0.399	4841.265	1.149	.2505
Trial-level knowledge: General knowledge	0.106	0.266	4089.603	0.397	.6913

suggests that it was the LPC to unknown-unfamiliar words that was more strongly modulated by domain knowledge, being somewhat larger for individuals with greater knowledge. We therefore examined the unknown-familiar and unknown-unfamiliar trials separately, in each case comparing a linear mixed-effects model incorporating HP knowledge as a predictor (Table S11) to a nested model with only an intercept term. For the unknown-familiar items, the simpler model was preferred ($\chi^2(1)=1.835$, $p=.176$). For the unknown-unfamiliar items, the complex model was marginally preferred ($\chi^2(1)=3.334$, $p<.068$). This suggests that the relationship between domain knowledge and LPCs for unknown endings may have been primarily driven by the unknown/unfamiliar trials.

Summary

Overall, LPCs were relatively enhanced for unknown compared to known trials and, among unknown trials, for familiar compared to unfamiliar trials. Moreover, these effects also depended on individuals' domain knowledge: for unknown trials, LPCs were more positive for those with relatively greater HP knowledge.

4 | DISCUSSION

We examined the influence of domain and trial-level knowledge on word-by-word sentence processing, testing whether domain knowledge primarily influences the processing of content that is relatively difficult to recall. Our results support this hypothesis: N400s (known to reflect access to semantic content) for unknown and thus unpredicted words were nonetheless modulated by domain knowledge, with reduced amplitudes seen for individuals with higher HP knowledge. Across all participants, we also observed graded effects of trial-level knowledge, with N400 amplitudes being largest for unknown trials later judged as unfamiliar, intermediate for unknown trials later judged as familiar, and smallest for known trials.

Post-N400 LPCs revealed a somewhat different pattern: unknown trials led to more positive-going potentials compared to known trials, with the unknown/familiar trials eliciting the largest positivities.[2] In addition, LPCs were modulated by HP domain knowledge for unknown trials, mostly driven by the unknown/unfamiliar trials. In the memory literature, LPCs vary with factors related to memory encoding and retrieval, being enhanced when words in memory lists have previously received deep processing and/or are subsequently correctly remembered (Paller et al., 1987; Rugg & Curran, 2007; Urbach et al., 2005). Our results suggest that domain knowledge had a real-time impact on such memory processes during our sentence comprehension task, perhaps allowing unknown information to be rapidly linked to existing knowledge structures. This pattern has also been suggested in the text comprehension literature, where sentence and clause wrap-up processes often take more time for more knowledgeable individuals (Chin et al., 2015) and may predict subsequent memory (reviewed in Stine-Morrow & McCall, 2022). These results can inform theories of how language processing unfolds in the moment and also how we learn from language by deeply encoding information to be retained over longer timespans.

4.1 | Consideration of component overlap between N400 and LPC potentials

We found that domain knowledge influenced N400s and LPCs, with both being more positive-going for individuals with greater HP knowledge. In addition, among the

[2]However, we recognize that only limited conclusions can be drawn based on this effect given that it may be due (at least in part) to the unknown-familiar trials eliciting reduced (more positive) N400 potentials compared to the unknown-unfamiliar trials; see the following section, *Consideration of component overlap between N400 and LPC potentials*.

unknown trials, a sense of familiarity was associated with more positive-going potentials in the N400 and LPC time periods. Because both of the LPC effects follow N400 effects of the same directional polarity, we cannot rule out ERP component overlap as accounting for at least some of the effects of domain knowledge and familiarity on LPC components.

Because similar factors may influence ERPs in not only the N400 but also the post-N400 time periods, component overlap is a frequent concern among ERP studies of language (e.g., Delogu et al., 2021). It is often difficult to dissociate the effects of variables related to meaning, such as a word's cloze probability in a sentence context and its semantic relation with words in the sentence, on N400 and post-N400 ERPs. As Delogu et al. point out, one way to mitigate the potential for component overlap from N400s to influence later positivities is to attempt to orthogonalize variables in designs where N400 potentials can be equated across conditions to examine effects on subsequent ERPs. However, given our design, this was not possible. We expected that the same variable, domain knowledge, would influence different processes indexed by N400s and by post-N400 late positivities. We hypothesized that on average, domain knowledge would lead to increased availability of contextually relevant information (i.e., mental/situation models of the text) and therefore lead to reduced N400 amplitudes even when individuals did not know and/or could not produce any given critical word. We also hypothesized that domain knowledge would influence LPCs, which are known to reflect episodic memory processes of encoding/recollection.

Although we cannot rule out the possibility that component overlap accounts for some of our effects, several indicators point to functionally separable effects of knowledge on N400s and LPCs in our study. For the effects of domain (HP) knowledge in particular, we do not think that component overlap is likely to be the sole reason for the effects of HP knowledge to continue beyond the N400 time period into the LPC time period. For one, we see different patterns in the N400 and LPC time periods as a function of trial-level familiarity judgments. Inspection of unknown trials judged as familiar versus unfamiliar suggests that effects of domain knowledge on N400s obtain across both trial types; however, the effect of domain knowledge on LPCs seems to be mainly driven by items deemed unfamiliar (Figure 6). This suggests that there is a different relationship between domain knowledge and the processing reflected in the N400 and post-N400 (LPC) time periods.

Findings from Troyer and Kutas (2020) also suggest that HP knowledge has dissociable influences on N400s and post-N400 positivities. In that study, LPCs to words that are not contextually supported completions of sentences (e.g., '*There is one main bank in the wizarding world. It is run by* <u>*Alohomora*</u>.') were enhanced for high-knowledge individuals relative to low-knowledge individuals, with no such modulation of domain knowledge during the N400 time period (with all individuals showing similarly large N400s). By contrast, words that were contextually supported continuations of sentences showed modulation by domain knowledge during the N400 time period but not the LPC time period. Combined with the current findings, this pattern of results suggests that domain knowledge seems to impact N400s in moments where prior knowledge can facilitate word processing. This may generally be the case for correct/contextually supported words, even when these may constitute "unknown" words that are not available for explicit free recall. In contrast, domain knowledge seems to impact processes indexed by LPCs in cases where explicit memory processes may be taxed, such as when incoming information is not contextually supported and new links need to be made (or updated) between incoming information and existing knowledge.

4.2 | Domain knowledge and the availability of mental models

For the first time, we show that N400 amplitudes to words are systematically modulated by domain knowledge in the absence of explicit word knowledge. Even when successful lexical prediction is unlikely, individuals seem able to activate some relevant information from long-term memory (as inferred from smaller N400 amplitudes) to the extent it is available to them based on their domain knowledge. In other words, our N400 findings suggest that individuals with greater HP expertise activate rich mental models based on their domain knowledge, and this knowledge rapidly influences word processing even when those specific words are not likely to have been readily available from long-term memory. In the present study, we did not directly assess the nature of the (partial) information that *was* available in these moments; however, combined with previous findings that individuals with greater domain knowledge seem to quickly activate information that is related to the sentence context via both event knowledge and overlapping semantic features with predictable words (Troyer & Kutas, 2020; Troyer et al., 2022), we expected that multiple types of schematically related information may have been activated, leading to the facilitated processing we observed on the N400. Indeed, it is possible that in some other moment, the same individuals who were unable to successfully provide the correct responses might have been able to recall the appropriate information. This seems particularly true for unknown trials subsequently judged as familiar.

Our study was not specifically designed to adjudicate among neurocomputational theories and models of N400s. However, our findings run counter to accounts on which prediction is strictly based on probabilistic word activation (e.g., Brothers & Kuperberg, 2021; see discussion in Kuperberg & Jaeger, 2016) and support theories that also incorporate preactivation of semantic feature-based or otherwise partial concepts spanning broad swaths of relevant knowledge—even for concepts that are linguistically unlikely to be encountered in the moment (Luke & Christianson, 2016; Metusalem et al., 2012, 2016; Szewczyk & Federmeier, 2022; Troyer & Kutas, 2020; Troyer et al., 2022).

Several recent computational models posit that N400s reflect information states of the language comprehension system not purely captured by linguistic probabilities of the sort quantified by cloze norming. For example, Rabovsky et al.'s (2018) model N400 amplitudes as reflecting differences in implicit knowledge states prior to and upon receipt of an incoming word. These knowledge states are said to reflect "all aspects of the event described by the sentence" (Rabovsky et al., 2018, p. 700) and are not based solely on linguistic probabilities. In their conceptualization, these knowledge states reflect information that goes beyond what is linguistically appropriate in the moment but is part of the overall event(s) described by the sentence (people, places, things, actions, and so on). Li and Ettinger (2023) model N400 amplitudes as reflecting information not just about a word's probability given the sentence context but also information about the relationship between the incoming word and likely upcoming sentence continuations. Their model favors an interpretation in which both N400s and post-N400 positivities reflect aspects of noisy-channel computation. That is, because people attempt to understand language under imperfect (noisy) environments, the linguistic system must be ready to revise imperfect language input for comprehension to proceed.

Our results suggest that immediate increased activation of interconnected semantic networks is what provides individuals with greater domain knowledge an advantage in processing even (explicitly) unknown words in the moment, as inferred from N400 effects on unknown words for relatively high- versus low-knowledge individuals in our study. Activation of semantic networks from long-term memory may be akin to what Rabovsky et al. (2018) refer to as implicit knowledge states, and is likely to differ, moment by moment, as individuals with more or less relevant background knowledge understand language. To our knowledge, variation in domain knowledge at the individual participant level is not currently explored in contemporary models of N400s. However, we expect that modeling differences in semantic networks (either directly or by manipulating the text corpora on which large language models are trained) would be a productive extension of such models.

Though reduced N400s are often viewed as facilitating processing, there are moments where easing processing due to greater knowledge may not actually be advantageous. As discussed briefly in the Introduction, comprehension may at times be hindered by the availability of rich knowledge structures, as when processing negation (Fischler et al., 1983) or in the case of memory intrusions (e.g., Castel et al., 2007; see also Hubbard et al., 2019). Nieuwland (2015) examined such an instance using the temporal terms *before* and *after*, which have been found to induce differential processing loads. In comparison to *After X, Y*, the construction *Before X, Y* is more difficult to process because it requires the comprehender to hold information in mind in a manner that does not accord with the described events' chronology. In addition, Nieuwland's sentences did or did not align with ground truth (*'Before/After the global economic crisis, securing a mortgage was easy/harder'*). For the easier "After" but not the more difficult "Before" sentences, N400 amplitudes to sentence-final critical words reflected facilitation in true sentences compared to false. The author's interpretation was that real-world knowledge (e.g., that mortgages did become harder to secure) was available and difficult to overcome during comprehension. Given the present results, we would expect that when greater domain knowledge is available, these effects would be even stronger, such that expertise might impede veridical comprehension in cases where linguistic input runs counter to domain knowledge.

Our findings are consistent with views in which words act as dynamic cues to meaning rather than static links to dictionary-like entries in a mental lexicon (Elman, 2009; Lupyan & Lewis, 2019; Rabovsky et al., 2018). On such accounts, word meaning is context-dependent, with words acting as operators over the state-space of semantic/long-term memory, which can shape the semantic space (i.e., mental model) under consideration. An incoming word which is included in and/or closely related to the current semantic space might not lead to a large change in a mental model going forward. By contrast, a word providing novel or otherwise informative and useful information might trigger updating of the state-space. In our study, a lack of explicit word knowledge at the trial level was associated with larger late positive components, and this was influenced both by domain knowledge and the extent to which the correct word later seemed familiar. This suggests that having partial knowledge (in the case of unknown/familiar trials) and/or related knowledge (in the case of domain knowledge) may engender the in-the-moment deep processing necessary for updating (current) mental models under construction and/or long-term memory representations. These findings are consistent with theories in which post-N400 LPCs (sometimes called P600s) reflect processes involved in updating mental models/representations in the moment (Brouwer et al., 2019; see also Li & Ettinger, 2023) and perhaps learning over the longer term (Turk et al., 2018). We hypothesize that such LPCs also might coincide with longer reading times if individuals read at their own pace. This would align well with eye-tracking data showing that individuals with greater domain knowledge slow down at moments when they are likely to be integrating incoming information with existing knowledge structures (Chin et al., 2015). Incorporating reading time into future studies also may provide further insights into trial-level variation in electrophysiology and may allow for further disentangling the dissociable effects of familiarity on N400s and LPCs.

In sum, our data paint a picture in which language comprehension processes take immediate advantage of available mental models derived from domain knowledge—at least for the young adult participants and sentence materials in the fictional world explored here. Domain knowledge had near-immediate effects on word processing in the N400 time period, even when words were unknown to individuals. Although we cannot conclusively determine the precise nature of the effects of domain knowledge on post-N400 processing due to the potential for component overlap, our results also point to systematic differences in a more explicit, active use of words as a function of domain knowledge. In the next section, we discuss the possible relationship between post-N400 LPCs, domain knowledge, and learning from language.

4.3 | Domain knowledge and learning during language comprehension

In some sense, examining variation in knowledge across individuals constitutes a cross-sectional study of how domain knowledge develops with experience as individuals continue to learn more about the domain, including the creation or strengthening of meaningful relationships between linguistic input and existing knowledge. In the language learning literature, linking novel linguistic input to existing knowledge structures includes both implicit and explicit processes taking place over time. Even with only minimal exposure to novel words, N400 brain potentials are sensitive to information about word form and meaning. In a study of English-speaking undergraduates learning French, N400 brain potentials were sensitive to word status (real word versus pseudoword) after about a mere 14 hours of classroom study—even though overt behavioral distinctions between words and pseudowords were at chance; after an additional ~50 hours of study, N400 amplitudes were also sensitive to aspects of word meaning, assessed via a priming task (McLaughlin et al., 2004). In another study, when novel words (English pseudowords) presented in constraining sentence contexts, they were rapidly integrated into existing semantic networks, as evidenced by N400 modulations recorded during a semantic priming task (Borovsky et al., 2012).

Although some word knowledge may thus be gleaned rapidly, the integration of novel words with extant semantic networks seems to take place over time and can benefit from repetition. For example, Batterink and Neville (2011) presented a discourse that contained pseudowords with either a consistent meaning (e.g., *meeves* always meant *clouds* over ten presentations) or an inconsistent meaning (*meeves* replaced ten different words). While there was a reduction in N400 amplitude over time overall, this N400 amplitude was further reduced for pseudowords in consistent contexts, likely reflecting facilitated access to (pseudo)word meaning that was strengthened with each pseudoword presentation. In addition, the consistent/meaningful pseudowords that were subsequently correctly remembered elicited relatively larger-amplitude late positive components, or LPCs, relative to words that were not successfully remembered. This was interpreted as reflecting participants' attempts to retrieve information about the previously instantiated contexts to better understand the word in the current context (see also Kuipers et al., 2017).

In our study, N400 modulations of domain knowledge for unknown completions/words (i.e., those not produced during the sentence completion task) were taken to reflect variation in access to conceptual knowledge—the sorts of information likely to be part of schematic knowledge available to individuals as a function of their overall knowledge of the HP domain. Given that reductions in N400s can reflect ease of access to both word form and meaning (e.g., DeLong et al., 2018; Laszlo & Federmeier, 2009), it is also possible that each word's lexical familiarity, as a function of each individual's domain knowledge, played some role in modulating these brain potentials. However, over half (about 55%) of the sentence completions were standard English words likely to be well-known to all participants, and all of the words were processed in rich sentential contexts specific to the narrative world of Harry Potter. Therefore, it seems most likely that variation in N400 amplitudes due to domain knowledge did indeed result from the differential availability of semantically related information as the words were being processed for meaning. Moreover, of the "unknown" trials, domain knowledge seemed to have a greater impact on N400s for trials judged as seeming familiar (once the appropriate—correct—word was provided during the ERP reading task). We presume that on these trials, individuals may have had access to some knowledge cued by the context even if they could not recall the critical word before seeing it in this particular instance, providing further support for the proposal that the meaningful relationship with contextual information was what drove variation in ERPs, rather than word familiarity alone.

Our findings also suggest that both domain knowledge and item familiarity (as inferred from judgments during the ERP task) have an influence on post-N400 LPCs. Participants first read and then completed sentence contexts that were missing the final word. Shortly after, they were provided with the correct sentence-final word during the ERP study. It is likely that this combination of tasks served as a learning experience such that participants were actively comparing their experience during the ERP task (including receipt of the correct critical word) to their preceding experience of attempting to produce the correct word during the sentence completion task. We observed large LPCs in exactly the cases where participants were likely to have partial (but incomplete) knowledge: for familiar trials (across all participants; Figure 5) and even among the unfamiliar trials for individuals with high HP knowledge (Figure 6). Given that LPCs reflect deep encoding and are frequently predictive of subsequent memory (recall or recognition), we hypothesize that these instances reflect cases where individuals are able to rapidly link word input to their existing knowledge, enabling them to strengthen connections and/or establish new ones within existing semantic networks. A related factor is that of motivation: high-knowledge individuals not only possess relevant background knowledge, but they also have been motivated to gain that knowledge. These individuals might therefore have been more motivated to deeply engage with the sentence materials in our study and to expand their knowledge. In future studies, we plan to explore the relationship between ERPs, domain knowledge, and downstream learning and memory. For example, if post-N400 LPCs are indeed a metric of long-term learning in our study (as they have been shown to be elsewhere; Turk et al., 2018), then we might expect to find that having high domain knowledge boosts in-the-moment processing (indexed by LPCs) as well as subsequent memory (assessed behaviorally) for items which had previously been unknown. This approach would also allow for functionally dissociating effects of domain knowledge processing reflected by N400s and LPCs.

4.4 | Conclusions

Our results illustrate the immediacy of prior/background knowledge in allowing relevant (though not explicitly available) information to be accessed and actively used during real-time language processing and comprehension. Our N400 findings provide novel evidence for the graded activation of conceptual information, which accompanies language comprehension in a manner that is likely implicit and perhaps even obligatory, occurring as a function of relevant available knowledge structures. Given that domain knowledge influenced processing on trials for which participants could not provide the appropriate sentence completion in the instant they were queried, this supports theories of linguistic preactivation that allow for the preactivation of word-related information that is not strictly lexical in nature. Our LPC results also suggest that our participants actively *used* this cued information—perhaps making an effort to commit information gleaned from linguistic input to memory—when knowledge structures were available. These results underscore the importance of considering individual differences in knowledge in models and theories of language comprehension. Future work using EEG and converging methods could examine how individual differences in knowledge contribute to learning in real time during language comprehension, which could shed additional light on the functional significance of the LPC during language processing.

Perhaps the most important aspect of our findings is that they highlight the variability inherent in language comprehension. Variability due to knowledge impacted obligatory aspects of language comprehension (such as the need to link sensory input to meaning) as well as additional processing that may optionally accompany language comprehension (e.g., updating working memory and/or long-term memory representations). In other words, domain knowledge can influence not only how readers access meaning but also how they use this meaning in the moment. These findings are in line with recent discussions of how variables like motivational states, goals, and task demands, among others, can shape different "modes" of language comprehension, including the extent to which individuals engage in relatively active compared to more passive comprehension (Christianson et al., 2022; Federmeier, 2021; Huettig & Ferreira, 2022).

Combined with our previous work, we consistently find evidence that among young college-aged adults, variation in domain knowledge leads to differences in the rapid impact of sentence context (Troyer & Kutas, 2018) as well as to the immediate availability of schematically related content (Troyer & Kutas, 2020; Troyer et al., 2022). Our results build on this and other work (Troyer et al., 2019) showing that access to unknown but domain-knowledge-related languages is facilitated for those with the available domain knowledge. Moreover, our LPC results begin to highlight how knowledge may also impact individuals' *use* of incoming language input in real time, raising the possibility that domain knowledge may have immediate consequences for how sentence meaning is learned and remembered, and that we can observe the moment-to-moment impact of existing domain knowledge on this process in real time.

AUTHOR CONTRIBUTIONS

Melissa Troyer: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; software; visualization; writing – original draft. **Marta Kutas:** Conceptualization; methodology; supervision; writing – review and editing. **Laura Batterink:** Methodology; supervision; writing – review and editing. **Ken McRae:** Conceptualization; funding acquisition; resources; supervision; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data available on request due to privacy/ethical restrictions.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Figure S1 A schematic of the experiment procedure. Participants first provided sentence completions to each of 172 sentence pairs describing fictional "facts" about Harry Potter (left panel). They next completed the EEG experiment (middle panel). Finally, they completed questionnaires about Harry Potter as well as other measures of individual differences (right panel).
FIGURE S2 Mean amplitudes for ERPs (top: N400 time period; bottom: LPC time period) are plotted as a function of each individual's HP knowledge (X axis) and number of trials (size and shading of bubble) for the Known, Unknown-familiar, and Unknown-Unfamiliar trials.
FIGURE S3 Grand average ERPs across all single trials to critical words are plotted across the whole head for Known, Unknown-Familiar, and Unknown-Unfamiliar trials. Electrode locations are shown on the head in the center.
TABLE S1 ROI analysis for N400 time period incorporating trial-level knowledge.
TABLE S2 ROI analysis for N400 time period incorporating trial-level knowledge and HP knowledge.
TABLE S3 ROI analysis for N400 time period for (a) known and (b) unknown trials.
TABLE S4 ROI analysis for N400 time period for unknown trials as a function of familiarity.
TABLE S5 ROI analysis for N400 time period for unknown trials as a function of familiarity and HP knowledge.
TABLE S6 ROI analysis for LPC time period incorporating trial-level knowledge.
TABLE S7 ROI analysis for LPC time period incorporating trial-level knowledge and HP knowledge.
TABLE S8 ROI analysis for LPC time period for (a) known and (b) unknown trials.
TABLE S9 ROI analysis for LPC time period for unknown trials as a function of familiarity.
TABLE S10 ROI analysis for LPC time period for unknown trials as a function of familiarity and HP knowledge.
TABLE S11 ROI analysis for LPC time period for unknown-unfamiliar trials as a function of HP knowledge.

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