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EMPIRICAL STUDY

Task Effects on Linguistic Complexity and Accuracy: A Large-Scale Learner Corpus Analysis Employing Natural Language Processing Techniques

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Large-scale learner corpora collected from online language learning platforms, such as the EF-Cambridge Open Language Database (EFCAMDAT), provide opportunities to analyze learner data at an unprecedented scale. However, interpreting the learner language in such corpora requires a precise understanding of tasks: How does the prompt and input of a task and its functional requirements influence task-based linguistic performance? This question is vital for making large-scale task-based corpora fruitful for second language acquisition research. We explore the issue through an analysis of selected tasks in EFCAMDAT and the complexity and accuracy of the language they elicit.

Keywords learner corpus; task complexity; complexity, accuracy, fluency (CAF); NLP; TBLT

Introduction

Learner corpus research has primarily relied on collecting and analyzing second language (L2) learner writings such as essays (Granger, 2008). The

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increasing use of online language learning platforms creates opportunities for collecting L2 data at an unprecedented scale, covering a wide range of contexts, for example, people all over the world working on tasks on their computer or tablet at home or elsewhere. The EF-Cambridge Open Language Database (EFCAMDAT; Geertzen, Alexopoulou, & Korhonen, 2014), as the data underlying the research presented in this article, gives access to 1.2 million learner writings at all proficiency levels of English, and the corpus continues to grow. Learner corpora can therefore provide second language acquisition (SLA) research with a potential empirical treasure trove. However, learner corpora like EFCAMDAT that are collected in an educational context also raise the fundamental question of how to identify and interpret the data, given the many interacting linguistic, instructional, and learner factors.

In this article we argue that a fruitful step forward is the collaboration between corpus linguists, SLA researchers, and computational linguists. We will exemplify this synergy through investigating task effects on learner language by applying natural language processing (NLP) and corpus-linguistic tools to test hypotheses formulated within a task-based approach to language teaching (TBLT). Evaluating hypotheses in learner corpora introduces challenges absent from the typical experimental paradigms used within TBLT research. Unlike experiments, corpora typically do not follow a research design dedicated to the evaluation of a specific hypothesis, because, by their very conception, corpora are resources to be used for a wide range of research questions. The interpretation therefore needs to tease apart the different linguistic, instructional, and learner factors that interact in shaping the corpus data.

In any learner corpus, the prompts and topics used to elicit the L2 samples shape the language that is represented in the corpus. Indeed, there is a recognition in the SLA literature that corpus-based developmental investigations need to control for task effects to ensure that the developmental trajectory is not skewed. Tracy-Ventura and Myles (2015) show how task effects can affect generalizations regarding the acquisition of imperfective forms if tasks do not provide sufficient opportunity for use of a variety of forms. Vyatkina (2012, p. 595) warns that task effects pose a "particularly severe threat to validity in longitudinal designs."

Task effects are widely recognized as an important aspect of learner language analysis—for L1 writing, see Huot (1990); for language assessment, see Bachman (1990), Biber and Conrad (2009), Biber, Gray, and Staples (2014), Hinkel (2009), and Weigle (2002); for instructed SLA, see Kormos (2011), Kuiken and Vedder (2008), and Way, Joiner, and Seaman (2000); and for computer-assisted language learning, see Quixal and Meurers (2016).

However, learner corpus research has generally not been linked to research investigating effects of task on L2 production (but cf. Gablasova, Brezina, McEnery, & Boyd, 2015; Ott, Ziai, & Meurers, 2012).

The first aim of this article is to provide a conceptual and methodological example of how to connect the analysis of task effects in learner corpora with insights from TBLT. We adopt task-based frameworks (e.g., the Cognition Hypothesis by Robinson, 1995) to characterize tasks used in EFCAMDAT so as to separate task effects from developmental trajectories. Our second goal is to illustrate the relevance of large-scale learner corpora as an empirical test bed for complementing experimental TBLT research, so as to empirically broaden and strengthen findings and situate results within a proficiency trajectory of data from large numbers of learners from around the globe with different language backgrounds working on a large number of tasks.

To achieve these goals we first examine how cognitive task complexity might affect the global complexity and accuracy of the elicited language in line with earlier work on complexity, accuracy, and fluency (CAF; cf. Housen & Kuiken, 2009; Michel, 2017; we here leave aside fluency, given our focus on writing). We then investigate individual language features that may be elicited by the task and the instructional focus, such as the vocabulary and grammatical features given in the task prompt or the focus of the teaching unit leading up to the task. This perspective relates to Loschky and Bley-Vroman's (1993) distinction between "natural," "useful," and "essential" structures. It also means we can develop learner corpora that allow us to reliably evaluate L2 knowledge as opposed to L2 use (Tracy-Ventura & Myles, 2015).

Last but not least, we aim to demonstrate the necessity of combining corpus linguistics with computational linguistics in order to enable the linguistic analysis (complexity, accuracy, lexical, and grammatical features) that is needed for modeling task effects and developmental trajectories in large corpora. NLP tools are needed to automatically extract the relevant linguistic features, structures, and patterns (Granger, Kraif, Ponton, Antoniadis, & Zampa, 2007; Meurers, 2012, 2015). The NLP analysis of learner language presents challenges waiting to be addressed, requiring more interdisciplinary collaboration (Meurers & Dickinson, 2017). In the meantime, state-of-the art NLP for native language can provide a first approximation of the potential usefulness in terms of supporting the effective identification of relevant subsets of data and extending the standard inventory of complexity measures currently used in CAF analyses. In sum, this article will argue for and exemplify the fruitful triangulation of corpus linguistic, computational linguistic, and task-based approaches to SLA research.

Combining TBLT With Learner Corpus Research

Among the many definitions of a task within TBLT (e.g., Ellis, 2003; Skehan, 1998), we here follow Samuda and Bygate (2008) who define a task as "a holistic activity, which engages language use in order to achieve some non-linguistic outcome while meeting a linguistic challenge, with the overall aim of promoting language learning, through process or product or both" (p. 69). This definition is well suited for the EFCAMDAT corpus as a collection of instructed writing activities.

One productive strand of task-based research is interested in how different design features such as task complexity affect linguistic performance. A central hypothesis of the Limited Attentional Capacity Model (Skehan, 1998) and the Cognition Hypothesis (Robinson, 1995) is that the cognitive complexity of a task will impact the complexity and accuracy of the language people use to meet the cognitive/communicative requirements of the task. Skehan distinguishes factors of code complexity (e.g., vocabulary load and variety), cognitive complexity (e.g., clarity and structure of information to process), and communicative stress (e.g., time pressure) of a task that will affect the linguistic complexity and accuracy of the elicited language. Specifically, he predicts that limitations in attentional resources will lead to competition between complexity and accuracy. Unlike Skehan, Robinson's (1995) Cognition Hypothesis assumes that learners can access multiple attentional pools. His triadic framework (Robinson & Gilabert, 2007) distinguishes task complexity features (e.g., number and similarity of elements to deal with, whether a task plays in the here and now or not, whether it involves reasoning and perspective taking) from task condition features (e.g., gender of conversational partners) and task difficulty (e.g., perceived task demands, related to individual differences such as aptitude). In contrast to Skehan, Robinson claims that some aspects of task complexity (e.g., higher reasoning demands) will promote both high linguistic complexity and accuracy because the higher cognitive load will trigger learners to activate and allocate attentional resources to the linguistic form of task performance. Despite a rich body of empirical research (Jackson & Suethanapornkul, 2013; Robinson, 2011), to date no overarching outcomes can be presented because the different studies have used a plethora of task complexity manipulations and an even larger number of complexity and accuracy measures hindering comparisons (Jackson & Suethanapornkul, 2013; Long, 2016). On the one hand, the meta-analysis based on nine comparable studies by Jackson and Suethanapornkul (2013) attests small increases in accuracy and a decrease in fluency, which is in line with the Cognition Hypothesis. On the other hand, complexity measures did neither lend support nor disconfirm Robinson's (1995) account.

In addition to task complexity, task type (e.g., narrative, argumentative) has been shown to impact in particular linguistic complexity (Bouwer, Béguin, Sanders, & van den Bergh, 2015; Foster & Skehan, 1996; Lu, 2011; Vyatkina, 2012; Yoon & Polio, 2016). Yoon and Polio (2016) suggest that the functional differences between task types are stronger than differences in cognitive complexity. The role of focused instruction has not been addressed systematically in learner corpus research. Yet, Vyatkina (2012) demonstrates that when an instructional unit targets a specific structure it is likely that a task prompt at the end of this unit will elicit that target structure—while the same prompt might elicit another structure following another instructional unit and target.

Our goal is to demonstrate that corpus-based developmental SLA research can significantly benefit from insights from TBLT providing a deeper understanding of how different task design features affect the language elicited. At the same time, corpora can complement experimental paradigms in TBLT. Experiments allow researchers to manipulate fine aspects of task design while controlling for others in order to test their hypotheses. However, they are constrained by limited data size. Conversely, corpus investigations are constrained by the fact that the task design does not follow the specific manipulations that would be needed for testing specific hypotheses because most learner corpus developers aim for resources that can be of more general use. Yet, they offer a much richer data source in terms of data size as well as diversity (proficiency, L1 backgrounds, etc.) and thus allow us to investigate how core design features of a task (e.g., task type) impact the language used by learners (Plonsky & Kim, 2016). Importantly, corpora allow us to situate task effects within the proficiency trajectory and therefore better understand their impact on L2 development (Jackson & Suethanapornkul, 2013; Norris & Ortega, 2009). In this article, we will test the specific predictions made based on task-based insights of the EFCAMDAT data for selected tasks.

Research Questions

Our goal is to investigate the impact of task design on elicited language. In particular: How do task design features and instructional focus affect the written language used by L2 learners when they try to meet the nonlinguistic goal of a task? Specifically, how does task complexity, task type, and/or instructional focus impact on the complexity and accuracy of the language use in global as well as specific features or structures?

We embed our main research question in the more general question of how learner language develops in a longitudinal corpus, grounding the task-based analysis of linguistic complexity and accuracy on a longitudinal analysis of

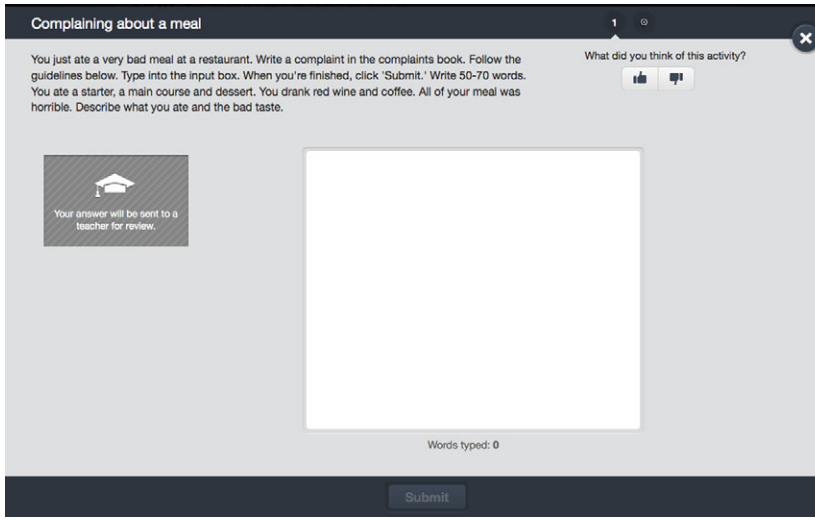

Figure 1 Englishtown Task 6.7: Complaining about a meal. [Color figure can be viewed at wileyonlinelibrary.com]

linguistic complexity across proficiency levels in EFCAMDAT. We finally ask if the observed task effects can be accounted for by the Limited Attentional Capacity Model (Skehan, 1998) and/or the Cognition Hypothesis (Robinson, 1995).

Method

The EFCAMDAT Corpus

We drew on EFCAMDAT, an open-access corpus available at http://corpus.mml.cam.ac.uk/efcamdat. The corpus consists of writings submitted to Englishtown, the online school of EF Education First. The Englishtown curriculum contains 16 levels, from A1 to C2 of the Common European Framework of Reference for Languages (CEFR). Each level consists of 8 units, each including a free writing task such as the one illustrated in Figure 1, summing to 128 distinct tasks.

The prerelease second version we used for this study contains 1,180,543 individual scripts. Script length ranges from 20–40 words at lower levels to 150–180 words at higher levels. There are 174,771 learners; 98,686 (56.5%) learners have written at least three scripts. Two thirds of scripts (787,010; 66.7%) include teacher corrections using a list of 24 error labels. National language background is used as an approximation of L1 (Geertzen et al., 2014). Further details of EFCAMDAT and Englishtown are available in Appendix S1 in the Supporting Information online.

Measures

Analyzing Accuracy

We exploit the 24 error labels in EFCAMDAT provided by EF teachers (Figure 6) to identify learner errors. Murakami (2014) used error labels in EFCAMDAT and successfully replicated findings on morpheme accuracy from the Cambridge Learner Corpus, which is manually error tagged using the sophisticated error annotation system of Nicholls (2003).

Among the many indices of accuracy (e.g., Foster & Wigglesworth, 2016; Polio, 1997; Polio & Shea, 2014), we calculate relative error frequency, which has been shown to successfully discriminate among learners of different proficiency levels (Hawkins & Filipović, 2012). Because error frequency is different from accuracy (Schachter & Celce-Murcia, 1977), we further calculated accuracy for two features, prepositions and past-tense verbs. As shown in the next section, the use of prepositions increases across proficiency while the use of past-tense verb forms decreases. These two features then allow us to investigate possible interactions between accuracy and use. To measure accuracy we calculated target-like use in obligatory contexts (Pica, 1983; see also Crosthwaite, 2016; Murakami & Alexopoulou, 2016).

First, we derived corrected texts in which incorrect portions were replaced with the corresponding corrected forms based on teacher corrections. We then annotated the original and corrected learner writings with part-of-speech tags using TreeTagger (Schmid, 1994) with the provided English model. The obligatory contexts of prepositions and past tense verbs were operationalized as the words tagged as "IN" and "VBD" in corrected writings, respectively. Finally, correct suppliances were counted by subtracting the number of omission and misformation errors from that of obligatory contexts. Capitalization errors and spelling errors were excluded.

Analyzing Complexity

While recent work suggests that more fine-grained measures might be more appropriate (Inoue, 2016; Lambert & Kormos, 2014), as a first step for establishing a common set of measures to capture global syntactic complexity, we adopted the suggestions in Norris and Ortega (2009) and used the following subconstructs:

1. An overall length-based metric: average sentence length (in words).
2. Subclausal complexity: mean length of clause (in words).
3. Subordination: subordinate clause per T-unit.

Average sentence length targets potentially multiclausal complexity of different types (e.g., through subordination, coordination, modification),

whereas mean clausal length targets subclausal complexity at the phrasal level. We do not report a measure of sentential coordination (suggested by Norris & Ortega, 2009) because automatic identification of such coordinations in EFCAMDAT was not reliable enough due to the multifaceted nature of coordination and its interplay with ellipsis.

To measure global lexical complexity, we use the Measure of Textual Lexical Diversity (MTLD; McCarthy & Jarvis, 2010):

4. MTLD: represents the mean number of sequential words that maintains a given threshold of type–token ratio in a text and was chosen over basic type–token measures to avoid their sensitivity to text length.

The complexity measures are computed using the freely available linguistic complexity code described in Vajjala and Meurers (2012), integrating the lexical and syntactic features of Lu (2010, 2012). We also computed a range of specific measures, which we will introduce in the analysis of task-type effects below. To date, we have not carried out a formal evaluation of the validity of individual measures, which also depend on the validity of the linguistic analyses provided by the native language NLP tools and the related conceptual issues (Meurers & Dickinson, 2017). However, prior studies have shown that native language taggers and parsers perform fairly well on the learner data in EFCAMDAT (Geertzen et al., 2014). For example, Alexopoulou, Geertzen, Korhonen, and Meurers (2015) evaluated the accuracy of extraction of relative clauses, reporting an *F* score of 83.9%, and found that state-of-the-art NLP tools provide reasonable quality.

Development of Complexity and Accuracy Across Proficiency

Increased complexity is often seen as an indication of the internalization of new structures, that is, new structural representations, while accuracy indicates acquisition of finer elements of newly acquired structures and their representations (Housen & Kuiken, 2009; Larsen-Freeman, 2006; Skehan, 2003). Documenting complexity and accuracy across the learning trajectory therefore to a certain extent can model the developmental trajectory of L2 acquisition.

Results of Complexity Analysis

We first consider the profile of our global measures of linguistic complexity and the patterns of accuracy across proficiency. Starting with average sentence length as overall length-based metric, Figure 2 shows the development across the 16 Englishtown levels and for 6 CEFR levels resulting from grouping

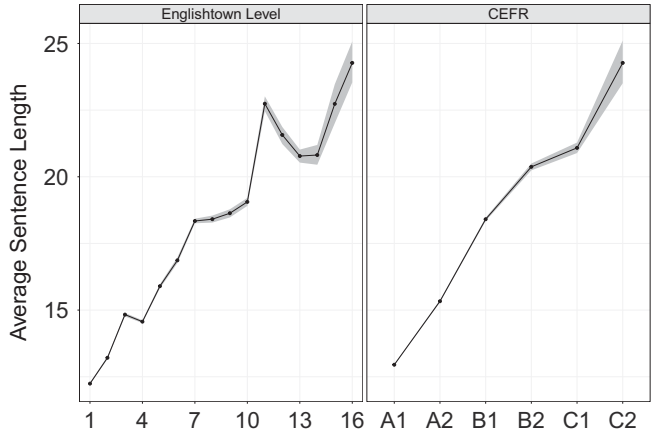

Figure 2 Average sentence length in words per Englishtown level (left) and CEFR aligned levels (right).

Englishtown levels as follows: 1–3 (A1),4–6 (A2), 7–9 (B1), 10–12 (B2), 13–15 (C1), 16 (C2).

Here and throughout this article, the grey shade indicates the 95% confidence intervals of the mean. The intervals are based on nonparametric bootstrapping with 1,000 bootstrap samples because Anderson-Darling tests implemented in the nortest package (Gross & Ligges, 2015) in R (R Core Team, 2016) suggested that the values did not distribute normally. The confidence intervals are generally wider at higher proficiency levels in Figures 2 through 9 because the number of writings is smaller at those levels and we can be less confident of the positions of the true values.

As expected, overall sentence length increases from beginner to advanced levels. Tapping into phrasal complexity (Norris & Ortega, 2009), mean length of clause in Figure 3 takes off at A2 and increases until B2 in the CEFR-aligned graph. The subordinate clause per T-unit in Figure 4 shows a sharp increase from beginner levels continuing until intermediate levels where it levels off (at B2), confirming earlier findings (Bardovi-Harlig & Bofman, 1989; Perkins, 1980; Scott, 1988). Lexical diversity measured by MTLD (Figure 5) grows steadily from the very early to the very advanced levels, but acquisition slows after B1. Generally, the individual Englishtown levels show more fluctuation, in particular for mean length of clause.

In sum, all global complexity measures increase across proficiency, though some differences in phasing can be observed.

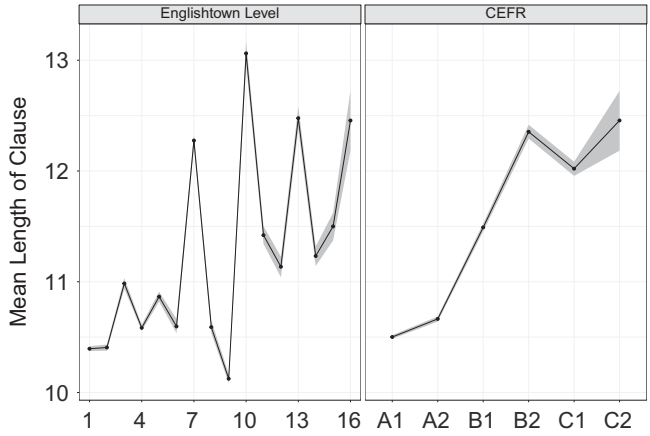

Figure 3 Mean length of clause in words across Englishtown (left) and CEFR-aligned levels (right).

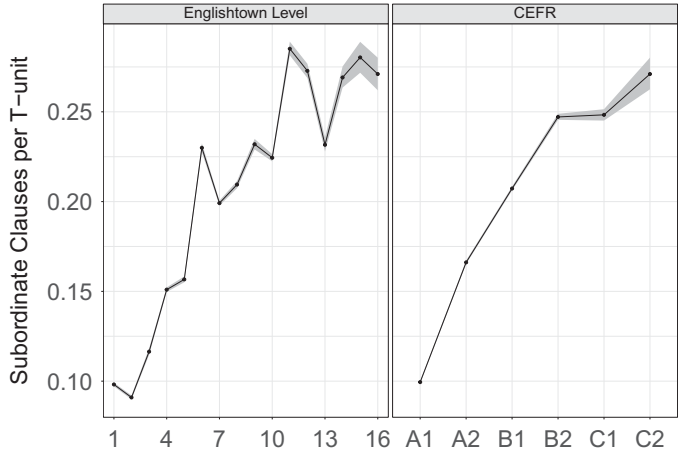

Figure 4 Subordinate clause per T-unit across Englishtown (left) and CEFR-aligned levels (right).

Results of Accuracy Analysis

Figure 6 shows the mean overall relative error frequency (left) and the mean relative error frequency across teacher error labels (right). The error rate generally drops as learners' proficiency advances. However, errors like phraseology (PH), possessive (PO), or verb tense (VT) show more fluctuation.

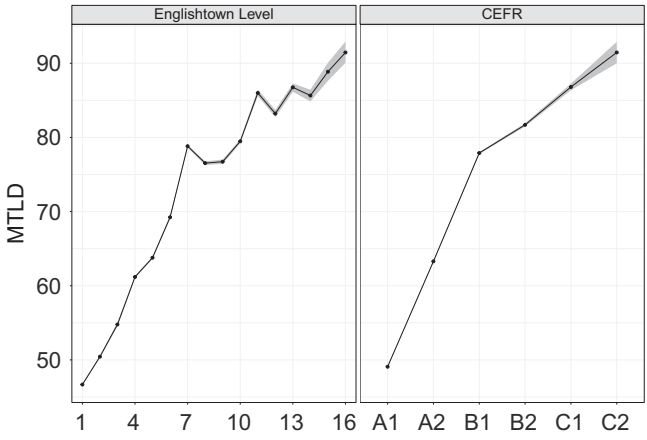

Figure 5 Measure of Textual Lexical Diversity across Englishtown (left) and CEFR-aligned levels (right).

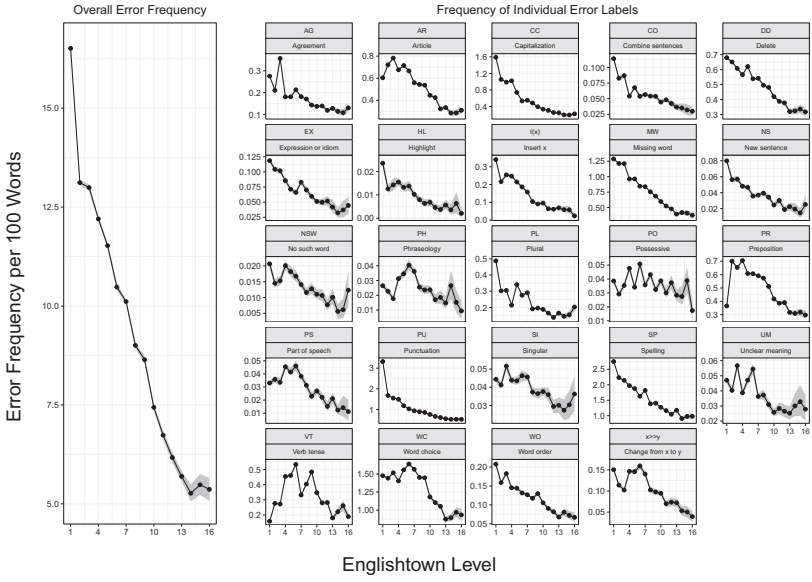

Figure 6 Error frequency across Englishtown levels.

As shown in Figure 7, the use of prepositions consistently increases from early beginner to advanced levels while the accuracy shown in Figure 9 suggests a U-shape pattern, dropping at level 5 to then increase until late intermediate (level 13). In other words, the initial increase in use gives rise to a

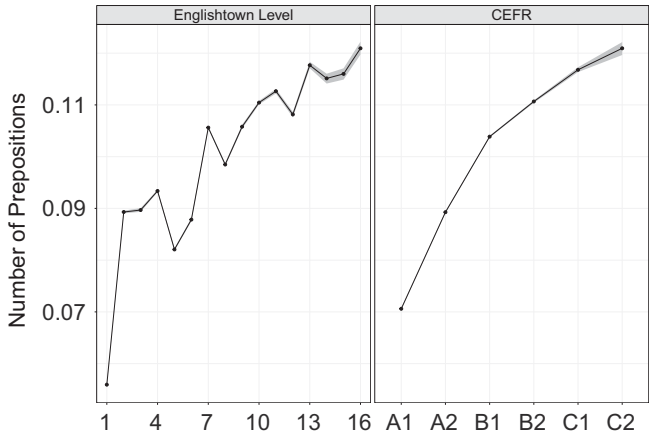

Figure 7 Number of prepositions across Englishtown (left) and CEFR-aligned levels (right) per number of words.

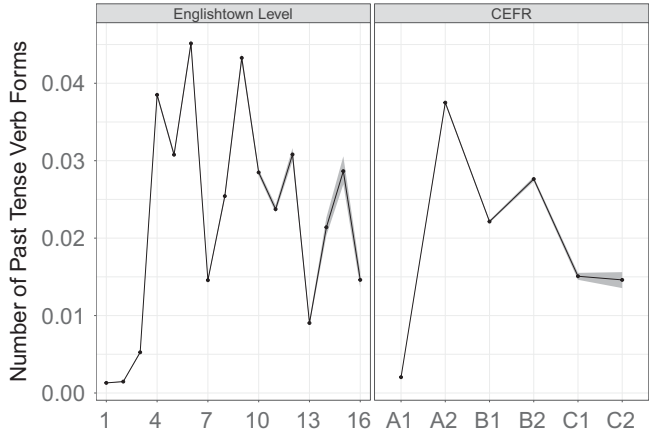

Figure 8 Number of past-tense verb forms across Englishtown (left) and CEFR-aligned levels (right) per number of words.

drop in accuracy that reaches a ceiling at around 95% at level 13. Past-tense use increases from Levels 2 through 4 (Figure 8), which is matched by the rise of accuracy (Figure 9). The comparison of these two features thus demonstrates that the extent to which relative frequency and accuracy correlate varies across linguistic features.

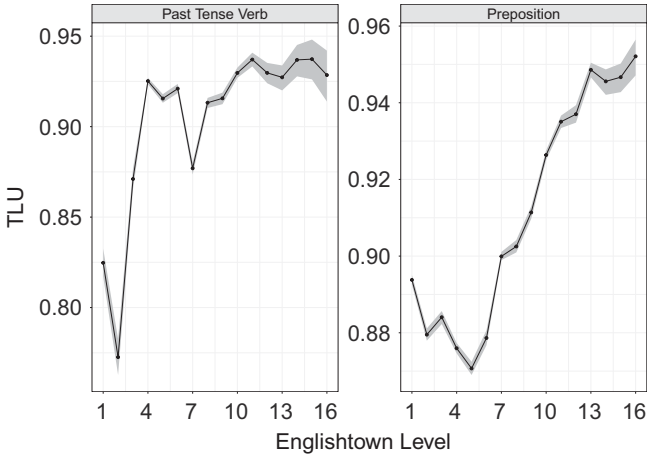

Figure 9 Accuracy of past-tense verbs (left) and prepositions (right) across Englishtown levels.

Effect of Task Design Features and Instructional Context

Three Pairs of Tasks: Narrative, Descriptive, and Professional Tasks

Broadly speaking, the writing activities contained in EFCAMDAT can be characterized as tasks, because L2 writers work toward a nonlinguistic outcome, for example, write a complaint or apply for a job, and are engaged in language use to achieve that goal (Samuda & Bygate, 2008). In this sense, EFCAMDAT can be seen as a task-based corpus. However, task design is not linked to any theoretical framework. Therefore, we cannot draw directly from EFCAMDAT tasks varying in specific parameters in a controlled and minimal way as is done typically in experimental designs. Nonetheless, the task-based frameworks provide us with categories and features that allow us to characterize EFCAMDAT tasks and evaluate a range of predictions regarding the influence of task design features on the elicited language. Figure 10 presents the six task prompts from intermediate learners (CEFR B1, Englishtown 6 and 7) we selected exemplifying three task types: narrative, descriptive, and professional. See Appendix S2 in the Supporting Information online for a more elaborate description of the tasks.

Table 1 summarizes the characteristics of the six tasks with reference to the Limited Attentional Capacity Model (Skehan, 1998) and the Cognition Hypothesis (Robinson & Gilabert, 2007). We explain the meaning of the labels used in Table 1 as we present the first narrative task, the "movie plot" (6.1), in comparison with the other tasks as needed.

Narrative tasks	
6.1 Writing a movie plot Decide what happens to John and Isabella. Write the final part of the story for your friend. … Write 50-70 words. (Beginning of story was given on former screen).	**7.4 Writing about a memorable experience** Reply to Tim. Use the notes to help you write and describing an interesting story from your past. … Write 70-100 words. (Tim's email about a memorable experience is visible next to the writing box).
Descriptive tasks	
6.7 Complaining about a meal You just ate a very bad meal at a restaurant. Write a complaint in the complaints book. Follow the guidelines below. … Write 50-70 words. You ate a starter, a main course and dessert. You drank red wine and coffee. All your meal was horrible. Describe what you ate and the bad taste (sic). See Figure 1.	**7.7 Writing a letter of complaint** Help your friend write her letter of complaint. … Write 70-100 words. Include the following information: (Leaflet advertising a cruise to Alaska is visible.)
Professional tasks	
6.4 Writing a resume Read the information in the internet job advertisement. Write your own personal resume for the job. … Write 50-70 words. (Job advertisement given on former screen.)	**7.3 Writing a job advertisement** You are leaving your current job and need to find a suitable replacement. Write an online job advert for your position. Use the text to help you. … Write 70-100 words. (Details of job requirements given as bullet pointed list in pull-out box.)

Figure 10 Task prompts.

In terms of Skehan's code complexity, both narratives create a high vocabulary load because all lexis needs to come from the learner. In contrast, the elaborate prompt of the holiday complaint (7.7) provides most of the vocabulary needed. Regarding cognitive complexity, the two narratives stand out for their fairly low structure and low to medium clarity because they are free writing tasks. By contrast, the professional tasks involve high structure because expectations about how a good résumé or a job ad looks like in terms of form and layout are genre specific (e.g., a bullet-pointed list). No vocabulary information is provided for the résumé (6.4), but for the job ad (7.3) most of the relevant lexis is given by the pull-out prompt, adding also to clarity and structure. As we do not hold information of how familiar writers are with a given task and under which conditions they were working, no characterization regarding cognitive familiarity and communicative stress is made here.

In light of the Cognition Hypothesis (Robinson & Gilabert, 2007) most tasks involve a high number of elements except for the job advertisement, which seems to be the simplest task in this respect. Regarding "here and now" versus "there and then," the movie plot is interesting because it plays in the "there," but the first part of the story presented to learners uses the present tense, which could be interpreted as "now."

Table 1 Overview of Task Characteristics

	Narrative		Descriptive		Professional	
Framework / Dimension of Task Complexity	**6.1 Continuing movie plot**	**7.4 Telling memorable experience**	**6.7 Complaint restaurant**	**7.7 Complaint cruise**	**6.4 Write resume**	**7.3 Write job advertisement**
Limited Attentional Capacity Model (Skehan, 1998)						
Code complexity	High voc.load	High voc.load	Medium voc.load	Low voc.load	High voc.load	Low voc.load
Cognitive complexity	Low structure and clarity	Low structure, medium clarity	Medium structure, high clarity	Medium structure, high clarity	High structure low clarity,	Medium structure, high clarity
Cognition Hypothesis (Robinson & Gilabert, 2007) resource-directing variables						
Number of elements	Many – different	Many – different	Medium – similar	Many – similar	Many – similar	Medium – different
Here & now	There & now	There & then	Here & now	There & then	Here & now	Here & now
Reasoning	Probably	Likely	No	Likely	No	No
Perspective taking	Yes	No	No	Yes	No	Yes

Telling a story (narratives) may well involve reasoning, while no reasoning is expected in the professional tasks because they primarily consist of factual statements (6.4) or the description of desirable applicants (7.3). The factor "perspective taking" is important for the continuation of the movie plot, because the point of view of the different characters in the story needs to be taken into account. In contrast, the memorable experience is a story told from the writer's perspective. The cruise complaint needs to be written for a friend and the job advertisement needs to take up the perspective of a job hunter.

Unlike experimental studies, this characterization of tasks is post hoc and therefore lacks the fine manipulations that would ideally be built on the theoretical underpinnings presented in the former sections. Moreover, many environmental factors, for example, the fact that learners worked in a digitally mediated context (Ziegler, 2016) could not be controlled for. However, these characterizations do capture some core properties of the tasks in question that are bound to impact on language use and allow us to form predictions regarding the expected language.

Predictions Based on Task Design Features

Skehan's (1998) code complexity singles out the cruise complaint (7.7) and the job ad (7.3) as two tasks with low vocabulary load, keeping cognitive resources available to focus on form (complexity and accuracy). This prediction might hold within (e.g., meal vs. cruise complaint) or across task types (e.g., job ad vs. movie plot).

Prediction 1: Higher accuracy and syntactic complexity for cruise complaint and job ad.

The high clarity and structure of the professional tasks are expected to increase accuracy because these characteristics ease cognitive demands and reduce processing pressure. The two narrative tasks with low clarity and structure are expected to show lower accuracy.

Prediction 2: High accuracy for professional tasks, low accuracy for narratives.

In terms of Robinson's Cognition Hypothesis, the cruise complaint letter is the most complex task (Table 1), therefore, it is predicted to elicit the most complex (syntax and lexis) and accurate language in contrast to the job ad and the restaurant complaint.

Prediction 3: Higher linguistic complexity and accuracy for cruise complaint, lower for restaurant complaint and job ad.

If we compare prediction 1 with prediction 3 we notice that they both predict high syntactic complexity for the cruise complaint, in particular in comparison to the restaurant complaint, but diverge regarding the job ad.

Predictions Based on Task Type and Instructional Focus

Narratives require writers to introduce entities, events, location (including ways to characterize them, modifiers, relative clauses), and linguistic means to link them to one another (including adverbs, e.g., firstly, secondly). The movie plot asks for a story about different people and will be mostly told in the third person, which is likely to cause more agreement errors.

Prediction 4a: Narratives will elicit referential phrases, modifiers, relative clauses, temporal and locative adverbs, and subordination. High numbers of agreement errors are likely.

The instructional focus of the preceding units and the respective prompt of the movie plot will elicit (mostly) present tense, while the memorable experience is more likely to elicit past tense (simple past vs. past continuous).

Prediction 4b: The movie plot will elicit (mostly) present tense, while the memorable experience mostly past tense (simple and continuous).

The Descriptive tasks (meal complaint, cruise complaint) are expected to elicit many copulas and predicative adjectives. The preceding instruction for both tasks focuses on the use of adjectives and, therefore, a high number of adjectives can be expected. The prompts are likely to elicit past tense. In terms of syntactic complexity, descriptive tasks can be expected to require simple (rather than complex) sentences linked through coordination rather than subordination.

Prediction 5: Descriptive tasks will elicit copulas, adjectives, low syntactic complexity, and past tense.

Given the formal setting of the Professional tasks (résumé, job ad) we expect high levels of lexical sophistication, that is, more infrequent words. A nominal style (lexical density, e.g., noun/verb ratio might be high) is likely, including complex noun phrases, while syntactic complexity outside nominals is predicted to be low due to list-like writings. Furthermore, we expect low numbers of agreement errors, due to an absence of many different persons acting.

Prediction 6: Professional tasks will elicit sophisticated lexis, nominal style and complexity, low syntactic complexity outside nominals, and a low number of agreement errors.

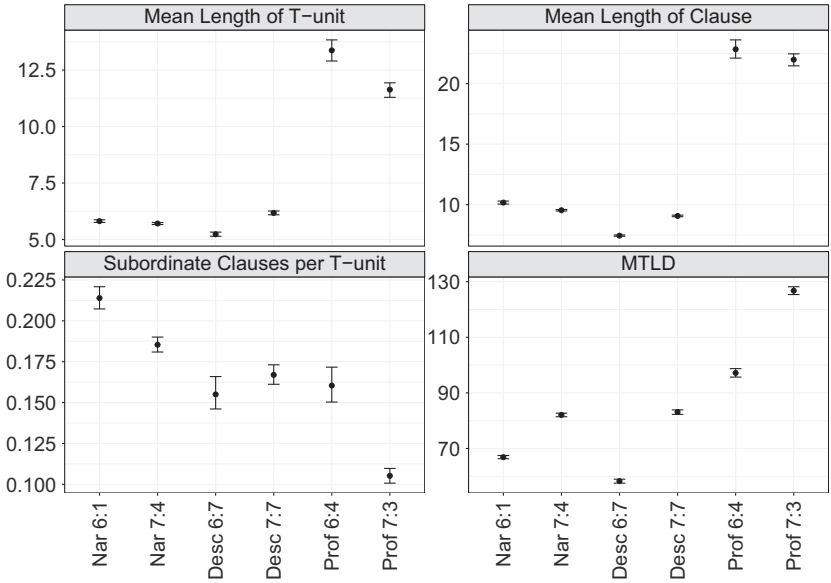

Figure 11 Global complexity measures per task: mean length of T unit (top left), mean length of clause (top right), subordinate clauses per T unit (bottom left) and Measure of Textual Lexical Diversity (bottom right).

Results

Global Measures of Complexity and Accuracy Per Task

Figure 11 shows global complexity measures for our six tasks, along with their bootstrap-based 95% confidence intervals. There are task effects with task type emerging as a key factor in some cases: for example, professional tasks pattern together for mean length of T unit and mean length of clause while narratives pair at the higher end of subordinate clauses per T unit. There is also variation cutting across task type as depicted in the graphs for MTLD and subordinate clauses.

Figure 12 depicts the mean relative error frequency of each error type (left), mean overall relative error frequency (top right), and the mean accuracy of prepositions and past-tense verbs (bottom right) for each of the target tasks. Again, we can visually grasp task effects on the rate of individual errors as well as the accuracy of prepositions and past tense.

Effects of Task Design Features on Linguistic Complexity and Accuracy

Due to their low code complexity (Skehan, 1998; cf. Prediction 1), the cruise complaint (7.7) and the job ad (7.3) should show relatively high

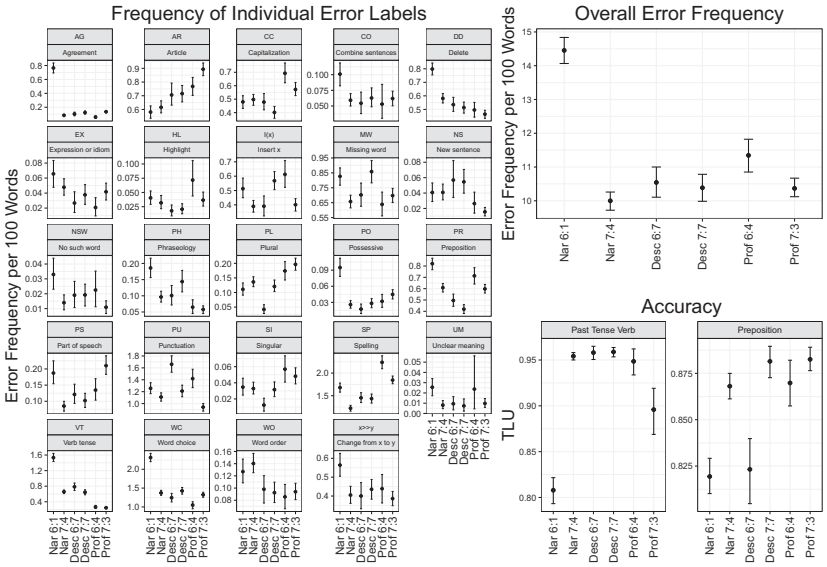

Figure 12 Error frequency and accuracy per task: mean relative error frequencies (left), mean overall relative error frequency (top right), and mean accuracy of past-tense verb and prepositions (bottom right).

syntactic complexity and accuracy. In Figure 11, task 7.3 is indeed eliciting highly complex language, with the highest score for lexical complexity and consistently high scores for the other complexity measures. The only exception is subordination, which was expected for list-like writings (Prediction 6). Prediction 1 is not confirmed, though, for the cruise complaint, which shows medium to low linguistic complexity. This fact also disconfirms Prediction 3, where we predicted high linguistic complexity for task 7.7 based on high cognitive complexity. When comparing code-complexity effects within task type, we see that the cruise complaint (7.7) indeed elicits more complex language than the restaurant complaint (6.7), confirming the prediction. Note that there is no increase in the relevant measures between levels 6 and 7 (Figures 2–5), indicating that the difference between 6.7 and 7.7 is not due to the higher proficiency of the latter. For 7.3, we might argue for lower overall error frequency, but 7.7 does not stand out in terms of accuracy.

The accuracy figures do not confirm Prediction 2. Even though the two professional tasks have low error rates and one of the two narratives stands out

for its high error frequency, the memorable experience and the résumé give rise to similar numbers.

Prediction 3, based on Robinson and Gilabert (2007), is confirmed for the meal complaint (6.7) and the job ad (7.3), which consistently elicit language of low complexity (except for subordination). Parallel effects on accuracy are visible for the job ad only in terms of overall error frequency and the use of prepositions. In contrast, Prediction 3 is in general disconfirmed for task 7.7. Yet, as the cruise complaint does indeed elicit more complex language than the meal complaint, Prediction 3 is confirmed within task type.

In sum, predictions for linguistic complexity were only partially confirmed and most apparent in relation to the simplest task (meal complaint) in terms of cognitive task complexity (Robinson & Gilabert, 2007), particularly, when comparing within—but not across—task types. Accuracy effects were less pronounced overall and could not be accounted for by task design features in this study.

Effects of Task Type and Instruction

We focus on narrative tasks for effects of task type and instruction, while only exemplary findings for descriptive and professional tasks are presented.

Two shortened random excerpts available below from the movie plot (6.1) and memorable experience (7.7) tasks illustrate Prediction 4a: high use of demonstratives, pronouns, possessives, and connectives to temporally link events; a variety of subordinate clauses to identify or describe referents and causation; and the use of present and past tense (task 6.1). Writers in task 7.7 use aspectual distinctions (simple past vs. past continuous) and because the story is told from the writer's perspective there are fewer anaphoric expressions.

1. Narrative 6.1: Movie plot Writing ID: 122619, L1: Brazilian
   Nothing was stronger than John's love. This poor boy was persuaded for Isabella that actually, was lesbian. [. . .] At the end, Isabella kills John using a poisoned sardine and finally, lives happily ever after with Sara, the one that she really loves.;)
2. Narrative 7.7: Memorable experience Writing ID: 271872, L1: Brazilian
   Dear Tim, When I was 10, in a weekend, I went with my family to my uncle's farm. In that place there was a big artificial lake. My family and relatives were in around it, while my brothers, cousins and I were swimming [. . .]

To capture referential cohesion in the six selected tasks, we used measures of Local and Global Argument Overlap (McNamara, Graesser, McCarthy, & Cai, 2014, p. 65), capturing that the same noun or pronoun occurs in two

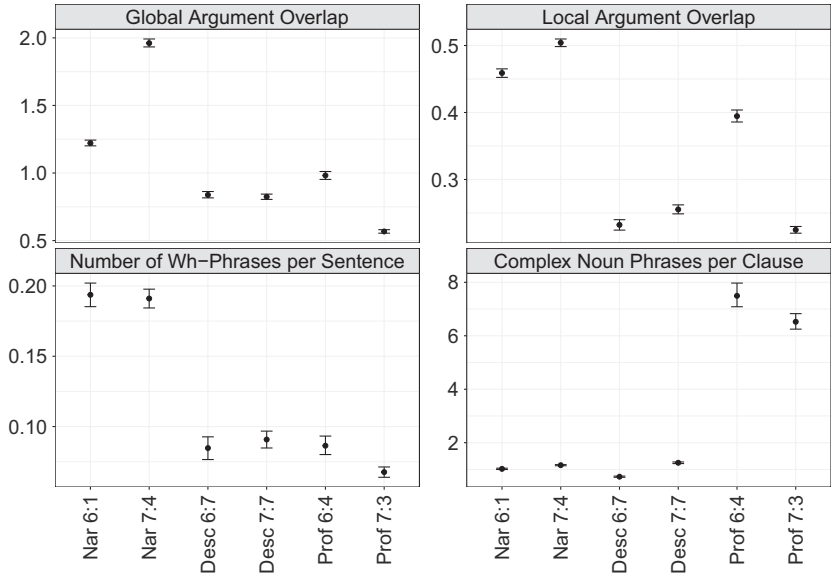

Figure 13 Top panel: Nominal discourse cohesion: global (left) and local (right) argument overlap count. Bottom panel: Number of wh-phrases per sentence (left) and Complex noun phrases per clause (right).

sentences, which in the local variant must be adjacent. As can be seen in the top graphs of Figure 13 both narratives score high in these measures. In accordance with Prediction 4, on syntactic measures narratives show high numbers of subordinate clauses (cf. Figure 11) and wh-phrases but low noun phrase complexity (cf. bottom graphs of Figure 13).

In accordance with Prediction (4a, b), we also found the movie plot to have high numbers of third person simple present forms, while the memorable experience elicited past tense (Figure 14). Confirming our expectation regarding third person *–s*, the movie plot has by far the largest relative frequency of agreement errors (see left panel in Figure 12).

Confirming Prediction 5, descriptive tasks elicit high numbers of adjectives, while scoring low on global (Figure 11) and specific (bottom graphs Figure 13) complexity measures. Figure 14 confirms that they elicit past tense. Finally, Prediction 6 for the professional tasks is largely confirmed. We see high numbers of complex nominals (bottom graphs Figure 13) and high global complexity except for subordinate clauses (Figure 11). The high number of gerundial forms seen in Figure 14 can be linked to the nominal style of this genre. Similarly, these tasks showed high scores on global lexical complexity (MTLD in Figure 11). In sum,

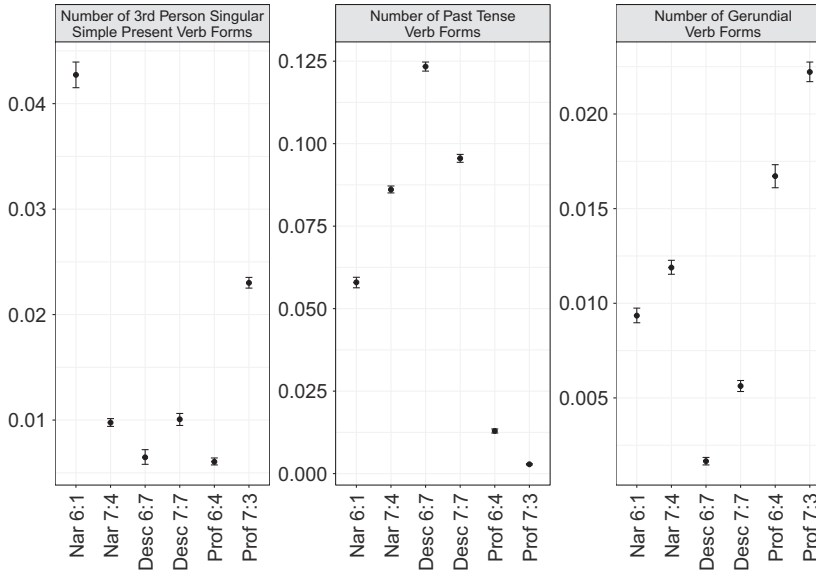

Figure 14 Number of third-person singular simple present verb forms (left), past-tense verb forms (center), and gerundial *–ing* forms (right).

the core predictions relating to effects of task type and instructional focus are confirmed.

General Discussion and Conclusion

The research background of this article is to develop and evaluate approaches and methods for exploiting learner corpora, in particular, the large amounts of data that online language learning technology is already making available to SLA research. The collaboration between corpus linguists, SLA researchers, and computational linguists is a necessary condition for this research program. In this article we explored this synergy through investigating task effects on learner language, as conceived within task-based frameworks. Our aim was twofold: first, to show that understanding of task effects and related TBLT insights is indispensable if we are to model learner language in large learner corpora and, second, to demonstrate that big corpora can contribute to TBLT research and complement the standard experimental paradigm. We focused on linguistic complexity and accuracy of language use.

The crucial contribution of a corpus like EFCAMDAT is the possibility of an analysis across proficiency and across tasks in a single design. We

presented such an analysis and were able to show that linguistic complexity and accuracy can characterize both development from early to advanced proficiency and tasks. Though not in itself surprising, this result is meant to demonstrate how the richness of learner corpora can enable multifactorial designs of a large scope. Our exploratory study is viewed as the first step to an extended investigation to better understand how the general picture obtained here is shaped by the interplay of varying factors such as L1, variability in the writings of individual learners across tasks and proficiency, variability in the effects of same task type (e.g., narrative) across proficiency, and so on.

We showed that linguistic complexity can model the language elicited by our three task types—narrative, descriptive, and professional—but that such modeling needs to employ a rich and diverse set of global and specific measures, for example, gerundial forms in Figure 14. Interestingly, some task-dependent features were not predicted. For example, the restaurant complaint task elicited a large number of irregular verbs, a probable consequence of the irregularity of verbs relating to food (e.g., eat, drink) and the copula. This is an example where corpus explorations can help identify naturally emerging structures in a task, potentially revealing essential, natural, and useful structures (Loschky & Bley-Vroman, 1993).

Task-based insights from this exploration are directly beneficial to researchers developing tasks targeting the elicitation of specific features or a variety of forms in order to evaluate the acquisition of specific grammatical phenomena (Tracy-Ventura & Myles, 2015). Identifying language forms elicited by specific task types can also highlight gaps in the features elicited in current corpora as well as complement experimental research (Gilquin & Gries, 2009). The contribution of NLP for an enriched inventory of reliable complexity measures is vital. For instance, the nominal discourse cohesion measures of local and global argument overlap distinguished the two narrative tasks (Figure 14) while we found that measures like Age of Acquisition also distinguish sharply between the three task types, an interesting and unexpected finding.

Our results bear on the ongoing debate regarding the relation between task type and task complexity, indicating that task complexity does indeed impact on linguistic complexity, but its effect is mainly visible within task type (e.g., simple vs. complex descriptive). When global complexity measures are considered (Figure 11), it is task type rather than task complexity that affects linguistic complexity, which confirms Yoon and Polio (2016). Yet, it may well be that the impact of task type is more readily detected in corpora exactly because finer aspects of task-design features cannot be controlled for. Error rate generally did not discriminate between tasks (again mirroring Yoon & Polio, 2016), but

accuracy of specific features did—although not in a predictable way. In the future, the interplay between complexity and accuracy (Skehan, 1998) could be clarified through an analysis of the variability of individual learner writings.

To conclude, this has been an exploratory investigation and comes with its limitations. As such, some of our results may be tentative or inconclusive. We have, nevertheless, demonstrated the kind of insights that can be gained through combining the developmental with the task-based perspective in the study of complexity and accuracy and the possibilities learner corpora and big learner data more generally open for wide-scope multifactorial designs that could tease apart the impact of distinct factors and yield rich inventories of features modelling development as well as tasks.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1. Further Details of EFCAMDAT
Appendix S2. Further Details of Individual Tasks.