Ideas cascade in parallel into keystrokes – modelling writing hesitations as finite mixture process

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Abstract

Classical serial models view the process of producing a text as a chain of discrete pauses, during which the next span of text is planned, and bursts of activity during which this text is output onto the page or computer screen. In contrast, semi-parallel models of writing assume that planning is not complete at production onset and operates in parallel with execution. Across six datasets from participants composing multi-sentence texts we instantiated these assumptions in two sets of Bayesian mixed effects models: (1) single-distribution models as assumed by the serial processing account, and (2) a finite (two-distribution) mixture model as assumed by the parallel processing account. We analysed interkey intervals at before-sentence, before word, and within word transitions. Model comparisons demonstrated strong evidence in favour of the parallel view across all datasets. When pausing occurred, sentence initial pauses were longer than word initial pauses which is consistent with the idea that larger linguistic edges are associated with higher level planning. However, we found – across populations – that interkey intervals at word and even at sentence boundaries were often too rapid to permit planning of what was written next. Our results cannot be explained by the serial processing but are in line with the semi-parallel view of writing.

Keywords: Cascading semi-parallel models; serial models; finite mixture models; Bayesian models; text composition; keystrokes

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Translating ideas into language involves a sequence of processes starting with communicative intent, proceeding through generation of a message, retrieving appropriate lexical items, deciding with which part of the message to start the utterance (which, depending on theoretical viewpoint (Bock & Ferreira, 2014; Wheeldon & Konopka, 2023), is determined by syntactic requirements of our language) and then retrieving orthographic and / or phonological codes, these are finally submitted to the motor programs that output speech, key or pen-strokes or signs (Olive, 2014; Van Galen, 1991; Wheeldon & Konopka, 2023).

The coordination of these processes in writing is arguably more demanding than in spoken language. This is because writing requires spelling retrieval, which may or may not be mediated by phonology, and the motor planning and execution required to press keys or move a pen. Pen control and typing skills are later-developing and more effortful than those required to articulate language sounds in speech and, possibly as a consequence, written output rate is typically slower (see for a recent review Kandel, 2023). Consequently mentally buffering of linguistic plans prior to output is likely to play a greater role in writing than in speech.

Written communication is also less time constrained: speaking comes with fluency requirements because hesitating during speech has a communicative effect (e.g. Clark & Fox Tree, 2002). There is therefore stronger pressure to plan ahead in speech than in writing (Roeser et al., 2019; Torrance & Nottbusch, 2012). Indeed writers can pause when they wish – even in the middle of a word – and for how long they want without compromising communication. Written production of multi-sentence texts – composing an argumentative essay, for example – therefore involves a combination for relatively fluent production bursts followed by pauses (Chenoweth & Hayes, 2001).

The study reported in this paper compares statistical models that instantiate two different theories of how cognitive planning processes are coordinated in writing. Through the analysis of 6 different datasets from writers of different ages and competencies composing multi-sentence texts, we compare these statistical models and therefore the cognitive models of text production onto which they map. Also, we evaluate competing predictions of these models by revisiting the often-reported finding that edges of larger linguistic units are associated with longer pauses (Conijn et al., 2019; Flower & Hayes, 1981; Matsuhashi, 1981; Wengelin, 2006). In what follows we first summarise previous research that has explored pause patterns in spontaneous text production. We then introduce two possible cognitive frameworks in which these can be interpreted. Finally we argue that analysis of pause-patterns at linguistic edges is necessary to permit differentiation between these two theories.

We focus on data form spontaneous text production (see Gernsbacher & Givón, 1995) for the following three reasons: First, text production such as essay, argumentative, and narrative writing in response to a writing brief or topic statement is a natural environment for text production (Dux Speltz et al., 2022; Dux Speltz & Chukharev-Hudilainen, 2021; Vandermeulen et al., 2023). Second, since the emergence of keystroke-logging software such as InputLog (Leijten & Van Waes, 2013) recording keystroke data during free text composition has become widely used among writing researchers and led to a rapidly expanding timecourse literature; for a recent special issue see Conijn and Torrance (2023).[1] These data are therefore important for contemporary theories of writing and freely available for statistical modelling and machine learning (Conijn et al., 2019; Conijn, 2020). Third, spontaneous text production is not constrained in the same way as it would be in experiments in which text is elicited in response to picture stimuli (Damian &

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[1] Social Science Citation Index reports 40 journal papers that describe research exploring composition processes using keystroke logging methods in 2022, compared to 26 in 2017 to 2019, and 7 in 2014 to 2016.

Stadthagen-Gonzalez, 2009; Meulemans et al., 2022; Nottbusch, 2010; Roeser et al., 2019) or is copied (Roeser et al., 2021; Van Waes et al., 2019, 2021). Instead the content-determination processes are free to run entirely internally, without the need to consult an image or a text that must be copied.[2]

Time intervals between adjacent keystrokes during typing vary as a function of various factors. Explaining the factors that influence the duration of inter-keystroke intervals (interkey intervals) requires a theory of how the various processes that transform intent into keypresses are structured. Planning what to say and how to say it may be serial. This means that the processing sequence operates one unit at a time. Under this theory, planning of the next language unit can only start when the previous unit has been fully processed, from communicative intention to completion of the written output. Therefore interkey intervals represent periods when the writer is planning what to write next: interkey interval will be longer at linguistic edges where planning scopes over larger text spans and their duration represents the time necessary to complete that planning (Alves & Limpo, 2015; Hayes, 2012; Kaufer et al., 1986; Matsuhashi, 1981; Schilperoord, 2002).

This serial account is consistent with the frequent finding that the average interkey interval duration immediately before larger linguistic units is longer compared to smaller linguistic units. For example, in spontaneous text the mean pause duration before a writer starts a sentence has typically been reported to be longer than before a mid-sentence word and these are, in turn, longer than between mid-word key presses (Deane & Zhang, 2015; Mohsen, 2021; Spelman Miller, 2006; Spelman Miller et al., 2008; Torrance, Rønneberg, et al., 2016; Wengelin, 2002; Xu & Qi, 2017). This is understood as being due to time needed to plan message and syntax for the next sentence, which is added to the time required to prepare the upcoming word, and the motor planning required to produce the first keystroke

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[2] Also, pauses in text production do not reflect visual encoding of the stimulus (although possibly reflect looking back during writing which we will return to in the discussion).

of that word (Baaijen et al., 2012; Medimorec et al., 2017; Medimorec & Risko, 2017; Roeser et al., 2019). However this account is not consistent with two other sets for findings:

First, writers and speakers can in principle plan utterances in full for one or multiple sentences before beginning to output words. However this is not what people typically do: utterances are not fully formed at production onset. Instead, syntax and lexical content and even details of the message itself are planned as the emergent result of a real-time process. For speech it is well known that the pre-planning duration depends – among other factors – on the need to avoid intra-sentential hesitations; speakers have a preference towards minimising language pre-planning depending on the extent to which upcoming words can be planned in parallel to production (Griffin, 2003; e.g. Levelt & Meyer, 2000; Wheeldon & Konopka, 2023). For writing, there is evidence that the time to keystroke / pen onset increases when a sentence starts with a more complex sentence-initial phrases similar as in speech [Nottbusch (2010); dam09; Roeser et al. (2019)]. For example, in Roeser et al. (2019) participants described moving arrays of images in simple utterances such as *A and the B moved above the C* that either started with a conjoined noun phrase (i.e. *A and the B moved*) or a simple noun (i.e., *A moved above the B and the C*). Importantly while the overall complexity of the utterance (in terms of length, number of phrases and noun) was held constant, sentences that started with a conjoined noun phrase increased the time to typing onset (and speech onset). This is not what one would expect if writers plan sentences in full before production onset. In fact, eye-movement data reported in Torrance and Nottbusch (2012) and Roeser et al. (2019) demonstrate that writers do not plan the lexical form of the utterance beyond the first noun before production onset (similar to speech Griffin, 2001, 2003), although there was evidence that lexical pre-planning of the second noun (i.e. *the B*) was more likely for conjoined noun phrases, i.e. when the second noun was part of the same phrase as the first noun.

Second, even though the average sentence-initial interkey interval tends to be longer,

they still tend to be very rapid. For example, Medimorec and Risko (2017) found that, in undergraduate students' writing on familiar topics 71% of sentence-initial interkey intervals were less than 1 seconds in duration. Also Rønneberg et al. (2022) reported that sentence-initial hesitations are rare, with over 50% of sentences preceded by very short pauses (around 430 msecs) and a mean of 1.2 seconds for the remainder of pauses. For comparison, these short pauses are less than mean written naming response latency for single objects (Torrance et al., 2018) in a similar population. Longer pauses in the remainder were similar to response latencies for short sentences when describing arrays of images (Roeser et al., 2019), also in a similar population. Despite the fact that writers can in principle pause when they want to, written composition is often remarkably fluent. The fact that these very short sentence-initial pauses exist, and in fact are quite common, is not consistent with the assumption that planning of the upcoming sentence is started and finished in the period between completion of the previous sentence and starting to write the next.

If utterances are not planned in full prior to writing onset, how is it possible that at least for reasonably competent writers compositing multi-sentence texts typically occurs remarkably fluently, with very few hesitations. The two examples above and similar findings point towards much of the mental activity associated with composition, including the relatively complex processing required to plan sentences, occurring as a result of a cascade of processes that operates partly in parallel and largely without executive control. Consistent with general trends in language processing theory (Bock & Ferreira, 2014; Chang et al., 2006; Dell et al., 2007), several researchers have argued that the processes associated with written production run at least in part in parallel (Bonin et al., 2012; Crump & Logan, 2010; Olive, 2014; Roux et al., 2013; Van Galen, 1991). Van Galen (1991), for example, argued for a cascade of modular processes each responsible for a specific transformation (semantic, syntactic, and so forth), with processing occurring as soon as information from the immediately upstream process becomes available (Christiansen & Chater, 2016). Buffers provide transient storage at each processing level to accommodate unsynchronised output

rates: when lower level processes lag behind higher level processes buffers allow fingers to catch up with message and language processing. Under this account when writers move from one sentence to another without hesitation this is due to then having completed required planning for the next sentence in parallel with output of the the sentence that they have just completed.

This semi-parallel cascaded account of the composition process therefore gives a rather different understanding of inter-keystroke intervals. Interkey intervals result from one of two sets of underlying mental processes. When upstream processes output at a rate equal to or faster than can be used for finger movement planning, then interkey intervals are determined just by the time needed for executing finger movements (i.e. just by processing below the last buffer in the processing cascade). However if one or more upstream processes provide output more slowly, then interkey intervals are determined just by time taken to complete upstream processes and not on finger movement. These two distinct data-generating processes mean that interkey intervals are a mixture of two distributions, one associated with the very rapid processing necessary for actioning keystrokes, and another that forms as a result of delays resulting from some combination of processing at the semantic, syntactic, lexical, or orthographic level not being complete at the time of the immediately preceding keystroke. (Roeser et al., 2021). The parallel account provides an explanation for why writers sometimes hesitate before sentence (or word) onset, but often do not. This is not because in some cases sentences are not planned, or planning was postponed until after sentence onset, but that this planning was completed in parallel with previous output.

Capturing this understanding of interkey intervals requires statistical models that are premised on more than one data-generating process. These models have been adopted in a number of psycholinguistic studies. For example, in language comprehension, Vasishth and colleagues (Vasishth, Jäger, et al., 2017; Vasishth, Chopin, et al., 2017) demonstrated

convincingly that some phenomena in online sentence comprehension observed in reading times are captured better by statistical models that assume that the underlying mental process that generates reading data is in fact a mixture of two process expressed as two distributions in the statistical implemental. In the context of written production Roeser et al. (2021) demonstrated[3] how models that allow the possibility of two underlying data-generating processes revealed two separate distributions when participants were copy-typing sentences or lists of words that are more pronounced for tasks with challenging orthographic sequences but reduced down to just one distribution in a tapping task where participants merely pressed two keys repeatedly as quickly as possible (e.g. "dkdkdkdk"). As argued by the authors, copy-typing underlies a similar cascade of processes as free text composition: copy-typing provides a typing context that is constrained to visual encoding of the target string and the retrieval of motor codes for letter combinations. For relatively experienced writers, visual encoding is likely to happen in parallel to writing (De Smet et al., 2018); hesitations occur when motor codes, for example for low frequency bigrams, were not retrieved in time (Roeser et al., 2021). However composition tasks are different from copy tasks: in copy tasks but not in spontaneous text production, content generation and grammatical encoding is artificially constrained to particular sequences of letter bigrams, words or sentences, and copy-typing involves a combination of visual encoding of the target string and mental buffering prior to the activation of motor codes. Typing hesitations in the context of copy-typing may – to some extent – reflect not just production but also, and possibly largely, visual encoding. Text composition, in contrast, provides data from the free generation of words and full sentences that is not dependent on a visually presented text stimulus. For these reasons our research extends the analysis of keystroke data using a mixture model approach to data from spontaneous text production.

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[3] For similar approaches see Almond et al. (2012), Baaijen et al. (2012), Chenu et al. (2014), Guo et al. (2018), Hall et al. (2022), Li (2021), and Van Waes et al. (2021).

Present Study

In the study that is presented in this paper we use Bayesian hierarchical models of keystroke intervals – similar to Roeser et al. (2021) – to identify whether the semi-parallel view of writing generalises to contexts in which participants compose texts. On the basis of these statistical models of text composition, we appraise to what extent linguistic edges (sentence and word boundaries) are associated with different pausing behaviours as frequently suggested in the literature (Ailhaud et al., 2016; Ailhaud & Chenu, 2017; Chukharev-Hudilainen et al., 2019; Conijn et al., 2019; Mohsen, 2021; Torrance, Rønneberg, et al., 2016; Wengelin, 2002).

The hypotheses are as follows: if the preparation of the upcoming production unit happens entirely at the corresponding linguistic edge as predicted by the serial account, and not in parallel to production, key-transition intervals can statistically be modelled as a function of the associated transition location. In other words, we expect interkey intervals to be proportionally longer at before-sentence locations compared to before-word locations compared to within-word locations. This is because transitions before larger linguistic units are associated with processing that involves higher levels of representation. The semi-parallel cascading view, in contrast, assumes that although interkey intervals at larger linguistic edges might be longer, it is in principle possible that writers do not (always) pause to plan their text but plan in parallel to writing. In other words, statistical models of the pause-and-burst view of written production do not capture that planning can operate, to some extent, in parallel to the output of the written production. Therefore, a statistical model that captures writing as a cascade of processes must account for the possibility that hesitations occur to some extent probabilistically across the entire text although some linguistic locations such as larger linguistic edges are associated with a higher pausing probability. We hypothesise that the statistical model of the parallel view provides a better out-of-sample generalisation than the implementation of the serial model of writing in the context of unconstrained

spontaneous text composition. We tested these models across 6 datasets.

For each dataset we evaluated four Bayesian statistical models. The first three models were premised on the (traditional) single-distribution understanding of interkey intervals. These models are consistent with the assumption that processing leading to a keystroke is fundamentally serial. In the first model we assumed the interkey intervals were drawn from a Gaussian (normal)distribution. In the second we assumed a log-Gaussian distribution. In both cases, consistent with previous studies that have modelled inter-keystroke intervals, we assumed equal variance across different linguistic edges (within words, at word boundaries, and at sentence boundaries). To provide a fairer comparison with the two-distribution model that followed we tested a third unequal variance model that allowed intervals associated with higher-order linguistic edges to have greater variability.

The fourth model was premised on the assumption that the processing that results in a keystroke runs, in part, in parallel with preceding output. As we have discussed, this model assumes two data-generating processes. We therefore followed the finite (two-distribution) mixture-modelling approach described by@roeser2021modelling. This model assumes that interkey intervals result from a mixture of: (1) uninhibited activation flow into motor programmes and (2) interruptions at higher levels that cause delays in this information flow. Therefore interkey intervals are not directly and sufficiently determined by transition location – as in the serial account – but are also associated with different probabilities that a hesitation occurs.

Methods

We analysed interkey intervals from six existing studies in which participants composed spontaneous, multi-sentence texts in response to writing prompts. The datasets include samples from populations with various writing experience and languages (e.g. young / L2 writers, students) performing different writing tasks (e.g. essays, syntheses). Datasets from a variety of different populations of writers and writing tasks were deliberately chosen

to challenge our modelling approach and to test to what extent pausing patterns generalise across writing contexts.

Data sets

Six datasets with keystroke data from free text production were used for analysis. An overview can be found in Table 1; descriptions below. Datasets used are C2l1 (Rønneberg et al., 2022), CATO (Torrance, Rønneberg, et al., 2016), GE2 (Ofstad Oxborough & Torrance, 2011), SPL2 (Torrance et al., n.d.), LIFT published in Vandermeulen, Steendam, et al. (2020) and described in Vandermeulen, De Maeyer, et al. (2020), and PLanTra published in Rossetti and Van Waes (2022b) and described in Rossetti and Van Waes (2022a).

Table 1

Datasets in brief.

Dataset	Source	Keylogger	Writing task	N	Mean age	Sample	Country	Language
C2L1	Rønneberg et al. (2022)	EyeWrite	Argumentative	126	11.80	6th graders	Norway	Norwegian
CATO	Torrance et al. (2016)	EyeWrite	Expository	52	16.90	Secondary school students (dyslexic, non dyslexic)	Norway	Norwegian
GE2	Torrance and Ofstad (n.d)	EyeWrite	Argumentative	45	19.00	Undergraduate students	UK	English
LIFT	Vandermeulen, Steendam, et al. (2020)	InputLog	Synthesis	658	17.00	Secondary school students	The Netherlands	Dutch
PLanTra	Rossetti and Van Waes (2022b)	InputLog	Text simplification	47	23.00	Master students	Belgium	English (L2)
SPL2	Torrance et al. (n.d.)	CyWrite	Argumentative	39	20.60	Undergraduate students	USA	English (L1) / Spanish (L2)

In C2L1 Norwegian 6th graders composed argumentative essays. In CATO upper Norwegian secondary students with and without dyslexia composed expository texts either normally or with masked letters to prevent writers reading their unfolding text. In SPL2 undergraduate students produced argumentative essays in their first language (L1; English) and in a second language L2 (Spanish) in which they were able to compose text but in which their mastery fell well behind their first language. Order of language (L1 / L2) and two writing prompts were counterbalanced. The LIFT data are from pre-university students producing argumentative and informative text syntheses on four topics each. The PLanTra data contains data from Master students in Business and Economics simplifying texts on sustainability, before and after receiving either online instruction on how to apply plain language principles to sustainability content or an online instruction exclusively on the topic of sustainability. The GE2 data are from Undergraduate students producing two argumentative essays on general-knowledge topics in either masked text or normal writing conditions, with masking, topic and order counterbalanced.

For C2L1, CATO, and GE2, keystroke data were captured using EyeWrite (Simpson & Torrance, 2007; Torrance, 2012). LIFT and PLanTra data were captured using InputLog (Leijten & Van Waes, 2013; Van Waes et al., 2019, 2021) and SPL2 data were collected using CyWrite (Chukharev-Hudilainen et al., 2019).

Data extraction

From the keystroke data we extracted interkey intervals between adjacent keys at locations that have been identified repeatedly in previous research as locations where observed mean interkey intervals (or counts of interkey intervals over a predetermined threshold) have tended to vary substantially (e.g. Chukharev-Hudilainen et al., 2019; De Smet et al., 2018; Torrance, Rønneberg, et al., 2016) and are detailed in Table 2. In particular we analysed the interkey intervals that resulted in the insertion of a character that started a new sentence (before-sentence transition); interkey intervals that started a new

Table 2

Transition location classification.

Transition type	Description	Example
Within word	Transitions between any letter	T^h^e c^a^t m^e^o^w^e^d. T^h^a^t[bsp][bsp]e^n i^t s^l^e^p^t.
Below word	Keypress after space followed by any letter	The ^cat ^meowed. That[bsp][bsp]en ^it ^slept.
Before sentence	Keypress following a space preceding any letter	The cat meowed. ^That[bsp][bsp]en it slept.

Note. '^' marks transition location; [bsp] represents backspace.

word (other than those at the beginning of a sentence; before-word transitions); and transitions between characters within words all transitions. At before-sentence locations, interkey intervals were timed to the shift keypress that resulted in the capitalization of the first key for most data sets (CATO, C2L1, SPL2, GE2) but were timed to the character key press in the PLanTra and LIFT datasets (i.e. the duration included the time to perform the capitalisting shift keypress); we return to this difference in the Results section. Transitions that occurred at the very start of the text or at the beginning of a paragraph were not treated as before-sentence transitions and were removed from the analysis. Importantly we also removed transitions that were followed by an editing operation. We therefore just modelled the times between keypresses in ongoing production.

We removed participants that did not complete all conditions in studies with within-participant factors (reducing the number of participants to 343 for LIFT data, and 41 participants for PLanTra data). We removed participants that produced fewer than 10 sentences (LIFT: 109 participants; PLanTra: 3 participants; SPL2: 1 participant). We further removed keystroke intervals that were too short to represent a behavioural response (≤ 50 msecs) or were of a length where such that they were unlikely to be associated with

ongoing text production ($\geq$ 30 secs); percentages can be found in Table 3. From the remaining data we randomly sampled a maximum of 100 observations per participant, condition, and transition location (when more than 100 were available). This was done to reduce the computation time of the Bayesian models required to complete sampling. For the LIFT data set we reduced the number of participants to 100 because the total sample was substantially larger than for the other datasets. Because the LIFT data set included the largest number of writing tasks, we sampled 50 observations per condition, location and participant which would otherwise exceed the computational resources available to us. The number of keystroke data used in the analysis can be found in Table 3.

Statistical modelling

We analysed keystroke data in a series of four Bayesian mixed-effects models. An overview of all models can be found in Table 4. Full modelling details can be found in Appendix A but we summarised the most relevant properties in this section.

Table 3

Data reduction. Mean percentage of extreme data removed and the mean percentage of randomly sampled data analysed by transition location ('–' if all data were used). Standard error in parentheses.

	Extreme values in %		Data analysed in %		
Dataset	$\leq$ 50 msecs	$\geq$ 30 secs	within word	before word	before sentence
C2L1	0.19 (0.1)	0.074 (0.063)	35 (2.6)	85 (1.8)	–
CATO	0.65 (0.15)	0.023 (0.016)	15 (0.95)	49 (2.2)	–
GE2	2.2 (0.17)	0.0072 (0.0055)	6.2 (0.43)	23 (1.4)	–
LIFT	2.6 (0.16)	0.0048 (0.0038)	3.2 (0.22)	13 (0.86)	99 (0.15)
PLanTra	2.5 (0.41)	0.04 (0.031)	9.7 (0.64)	37 (1.9)	–
SPL2	2.3 (0.2)	0.028 (0.016)	5.7 (0.39)	23 (1.4)	–

Table 4

Model overview. All models included by-participant random effect.

Models	Description
Serial	
M1	Single Gaussian model with effects of transition location (and experiment-specific manipulation).
M2	Single distribution log-Gaussian model equivialent to M1.
M3	Equivalent to M2 but with different variance components for each transition location (unequal variance).
Parallel	
M4	Two-distributions mixture of log-Gaussians for fluent interkey intervals and hesitant / disfluent interkey intervals; the distribution of hesitant keystroke intervals assumes – similar to M3 – different values for transition locations but the distribution of fluent intervals does not.

The first three models – models M1, M2, and M3 – were single-distribution models consistent with the serial account. They were single distribution models, with fixed effects for each combination of transition location and dataset-specific manipulations. Models M1 (Guassian) and M2 (log-Guassian) are consistent with standard models used in the literature and therefore serve as baseline models. For model M3 we relaxed the equal-variance assumption for transition locations, thus allowing transition locations on larger linguistic boundaries to assume a larger standard deviation; see Appendix A for rationale.

Model M4 is two-distribution mixture models consistent with the parallel cascading account. This model assumes that keystroke data result from a combination of two data generating processes; these models are referred to as finite mixture models in the literature (Gelman et al., 2014; MacLahlan & Peel, 2000). Both single-distribution models and the

two-distribution mixture model capture that processing difficulty at higher levels of activation leads to longer pauses but only the two-distribution model captures that planning-related pauses may occur at any interkey interval, even mid-word, and that planning may not be reflected in sentence or word-initial pauses when planning happens in parallel to output. In other words, instead of assuming that there is one process that shifts the distribution of transition durations for larger linguistic edges, we allow for the possibility that key-transitions at larger linguistic edges are more likely to reflect processing delays but the cognitive system does not obligate planning to occur before sentences or words. This is achieved by modelling interkey intervals as coming from a weighted mixture of two distributions associated with two different states, illustrated in equation 1:

1. Information from upstream mental processes can flow into keystrokes without interruption at intermediate levels. These fluent keystroke transitions are merely constrained by a person's ability to move their finger. Fluent interkey intervals (i.e. typing speed) are captured by the β parameter. β is represented in both log-Gaussian distributions in equation 1 referring to the same unknown parameter.

2. Any interruption at upstream levels of mental representation delays the information flow reflected in a resulting lag between keystroke intervals, for example when words or their spelling could not be retrieved in time. The slowdown for such hesitations is captured by δ and its frequency by the mixing proportion θ. The slowdown δ was allowed to vary by transition locations because hesitations at larger linguistic units are likely to be associated with higher level planning which causes longer delays in the output. The δ parameter was constrained to be positive, so that it captures how much longer hesitant interkey intervals are in addition to β.

$$
\begin{aligned}
\text{iki}_i \sim\ & \theta_{\text{location[i], participant[i]}} \times \text{LogN}(\beta + \delta_{\text{location[i]}} + u_{\text{participant[i]}}, \sigma^2_{e'_{\text{location[i]}}}) + \\
& (1 - \theta_{\text{location[i], participant[i]}}) \times \text{LogN}(\beta + u_{\text{participant[i]}}, \sigma^2_{e_{\text{location[i]}}}) \\
\text{where:}\ & u_{\text{participant}} \sim \text{N}(0, \sigma^2_{\text{p}}) \\
\text{constraint:}\ & \delta, \sigma^2_e, \sigma^2_{e'}, \sigma^2_{\text{p}} > 0 \\
& \sigma^2_{e'} > \sigma^2_e \\
& 0 < \theta < 1
\end{aligned}
\tag{1}
$$

The first line of equation 1 represents the distribution of hesitant interkey intervals that include the δ parameter presenting the slowdown for hesitant transitions; the second line represents the distribution of fluent – uninterrupted – interkey intervals that is characterised by β which is also present in the first file. Either of these two distributions is associated with the mixing proportion θ that ranges between 0 and 1. θ was parameterised here to represent the probability that an interkey interval is associated with the distribution of hesitant transitions. This probability is inversely related to the mixing weight of the distribution of fluent transitions by $1 - \theta$. In other words, a larger weight for either distribution inevitably means a lower weight for the other. We call this parameter the probability of hesitant interkey intervals. When a parameter is allowed to vary by transition location (levels: before sentence, before word, within word), this was indicated as subscript; similar for participants. For example, $\theta_{\text{location[i], participant[i]}}$ means that the mixing proportion θ is allowed to take on a different value for both the transition location and participant associated with the ith keystroke interval $i \cdots \in N$ where N is the total number of keystroke intervals. Because the hesitation probability was allowed to vary by participants as well as location type, we included a hyper-parameter for the mixing proportion θ for each transition location.

As with model M3, M4 allowed the variance associated with the key-intervals indicated as $\sigma^2_{e'}$ to vary by transition location. Further each of the two distributions in M4 had its own variance constrained such that the variance associated with the distribution of

hesitant keystrokes $\sigma_{e'}^2$ was larger than the distribution of fluent keystroke intervals σ_e^2. This is important because slower human behaviour similar to hesitant keystroke transitions is generally known to be associated with a larger variability (Schöner, 2002; Wagenmakers & Brown, 2007; Wing & Kristofferson, 1973). Model M4 and all other models included a random intercepts term $u_{\text{participants}}$ for participants which is constrained to be distributed around 0 with an unknown standard deviation, i.e. $N(0, \sigma_{\text{p}}^2)$, hence indicating participant specific deviations from the average typing speed β.

All models were implemented in the Bayesian framework (Gelman et al., 2014; McElreath, 2016). In the present analysis, we used weakly informative priors to aid model convergence by constraining the parameter space to plausible values (see e.g. Lambert, 2018; McElreath, 2016). Also, as the sample size of most of our datasets is large, weakly informative priors have no or a negligible effect on the posterior. Stan code for mixture models was based on Roeser et al. (2021; see also Vasishth, Chopin, et al., 2017; Vasishth, Jäger, et al., 2017) and can be found on OSF (https://osf.io/z65dw/); for a tutorial see https://rpubs.com/jensroes/mixture-models-tutorial.[4]

To compare the out-of-sample predictive performance of our models we used leave-one-out cross-validation based on Pareto smoothed importance-sampling (Vehtari et al., 2015, 2017). Predictive performance was estimated as the sum of the expected log predictive density ($\widehat{elpd}$) and compared by the difference between models $\Delta\widehat{elpd}$. We also summarised this difference as normalised over its standard error $|\frac{\Delta\widehat{elpd}}{\text{SE}}|$, hence the z-score of the difference between models (Sivula et al., 2020). Similar to other cross-validation techniques,

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[4] The R (R Core Team, 2020) package rstan (Stan Development Team, 2018) was used to interface with the probabilistic programming language Stan (Carpenter et al., 2016) which was used to implement all models. Models were run with 20,000 iterations on 3 chains with a warm-up of 10,000 iterations and no thinning. Model convergence was confirmed by the Rubin-Gelman statistic ($\hat{R} = 1$) (Gelman & Rubin, 1992) and inspection of the Markov chain Monte Carlo chains. The predictive performance of our models was compared using leave-one-out cross-validation (Sivula et al., 2020; Vehtari et al., 2015, 2017).

the advantage of leave-one-out cross-validation is that more complex models – models with more parameters – are penalised to prevent overfit.

Results

Model comparisons

The differences in the predictive performance of models for all datasets are shown in Table 5. For all six dataset the two-distributions mixture model (M4) provided greater predictive performance than all three single-distribution models. Differences in predictive performance ($\Delta\widehat{elpd}$) between models M4 and the nearest competing single-distribution model (M3) ranged between [18, 40] standard errors, indicating a substantially higher predictive performance for the two-distributions model. Among the single distribution models we found higher predictive performance for the unequal variance model and the lowest predictive performance for the single distribution Gaussian. Comparisons showing the fit of model predictions to the data can be found in Appendix B and echo the findings in Table 5. Data predicted by the two-distribution mixture model closely align with the observed data; data predicted by single distribution Gaussian models showed an inferior fit to the data.

Table 5

Model comparisons. Models were compared incrementally from the simplest to the most complex model. The comparison is shown along with the distribution type of model with the higher predictive performance. A negative difference in $\Delta\widehat{elpd}$ indicates higher predictive performance for the more complex model. Standard error is shown in parentheses.

Dataset	Mixture of two log-Gaussians (M3 – M4)	Single log-Gaussian (unequal variance; M2 – M3)	Single log-Gaussian (M1 – M2)
C2L1	-1,637 (72)	-38,301 (823)	-37,517 (798)

Table 5 continued

Dataset	Mixture of two log-Gaussians (M3 – M4)	Single log-Gaussian (unequal variance; M2 – M3)	Single log-Gaussian (M1 – M2)
CATO	-1,782 (75)	-38,972 (913)	-37,673 (881)
GE2	-2,427 (92)	-41,155 (653)	-38,843 (616)
LIFT	-5,105 (127)	-76,961 (1,656)	-74,851 (1,624)
PLanTra	-2,384 (90)	-35,204 (556)	-33,823 (526)
SPL2	-1,181 (64)	-30,430 (450)	-28,717 (418)

Note. $\Delta \widehat{elpd}$ = difference in predictive performance – estimated as expected log pointwise predictive density

Transition location effect

Figure 1 illustrates the mixture model results for every dataset: for each interkey interval we obtained two posterior probability distributions, one associated with fluent transitions between keys and another for interkey intervals where upstream difficulty resulted in hesitant interkey intervals. The hesitation probability – the probability of interkey intervals associated with hesitations – is indicated as the height of the distribution shown in yellow (on the right of each panel). The transition locations are characterised by the hesitation parameters: as we illustrate the mixture model, the distributions of fluent transitions – indicated in grey – are constant across transition location (within each dataset) but their height differs as the probability of fluent interkey intervals is the inverse of the height of hesitant interkey intervals; i.e. $1 - \theta$. Within-word interkey intervals have a negligibly small hesitation probability barely visible in the visualisation. Hesitations before words and sentences are both roughly equally likely than fluent transitions. In other words,

half of the time participants did not pause before a word or sentence; we explore this below. However, when hesitations occurred, these are longer at before-sentence interkey intervals compared to before word interkey intervals. The slowdown for hesitant interkey intervals – represented earlier as δ – is the distance between the distribution of fluent interkey intervals (β) shown in grey and the distribution of hesitant interkey intervals shown in yellow.

Figure 1 highlighted how model parameters relate to each other in pairs of distributions but to compare the effect of transition location on model parameters we need to compare the posterior distribution of the three parameters of interest individually. Therefore Figure 2 visualises the same posterior as Figure 1 but expressed directly in terms of posterior probability distributions of the individual mixture-model parameters. These are shown for all datasets by transition location. Although models were fitted with all dataset-specific conditions, we aggregated the posterior across conditions[5], and excluded conditions that might confound comparisons[6]. For posteriors of all conditions within datasets see Appendix F. The resulting posterior allows us to examine differences and similarities associated with transition locations for all datasets. In particular we can see how transition location in the text is associated with hesitant interkey intervals and hesitation probability. For completeness we also report the estimate for fluent interkey intervals.

Figure 2 shows largely the same patterns (with caveats) for all datasets. We summarise the evidence for differences between transitions locations in Table 6. We found that hesitations were more frequent – higher hesitation probability – before words than within words (BFs > 100 for all datasets) but only for half of the datasets hesitation

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[5] We aggregated across pre and post tests for the PLanTra dataset as well as genre and topic of the LIFT data set. We demonstrate in Appendix G and H, respectively, that there is negligible evidence for differences between these conditions.

[6] We removed the masked writing condition in the GE2 and CATO, the dyslexic group in the CATO data set, and L2 writing in the SPL2 data set. There was evidence for L2 writing effects (see Appendix D); evidence for marking effects was weak (see Appendix E).
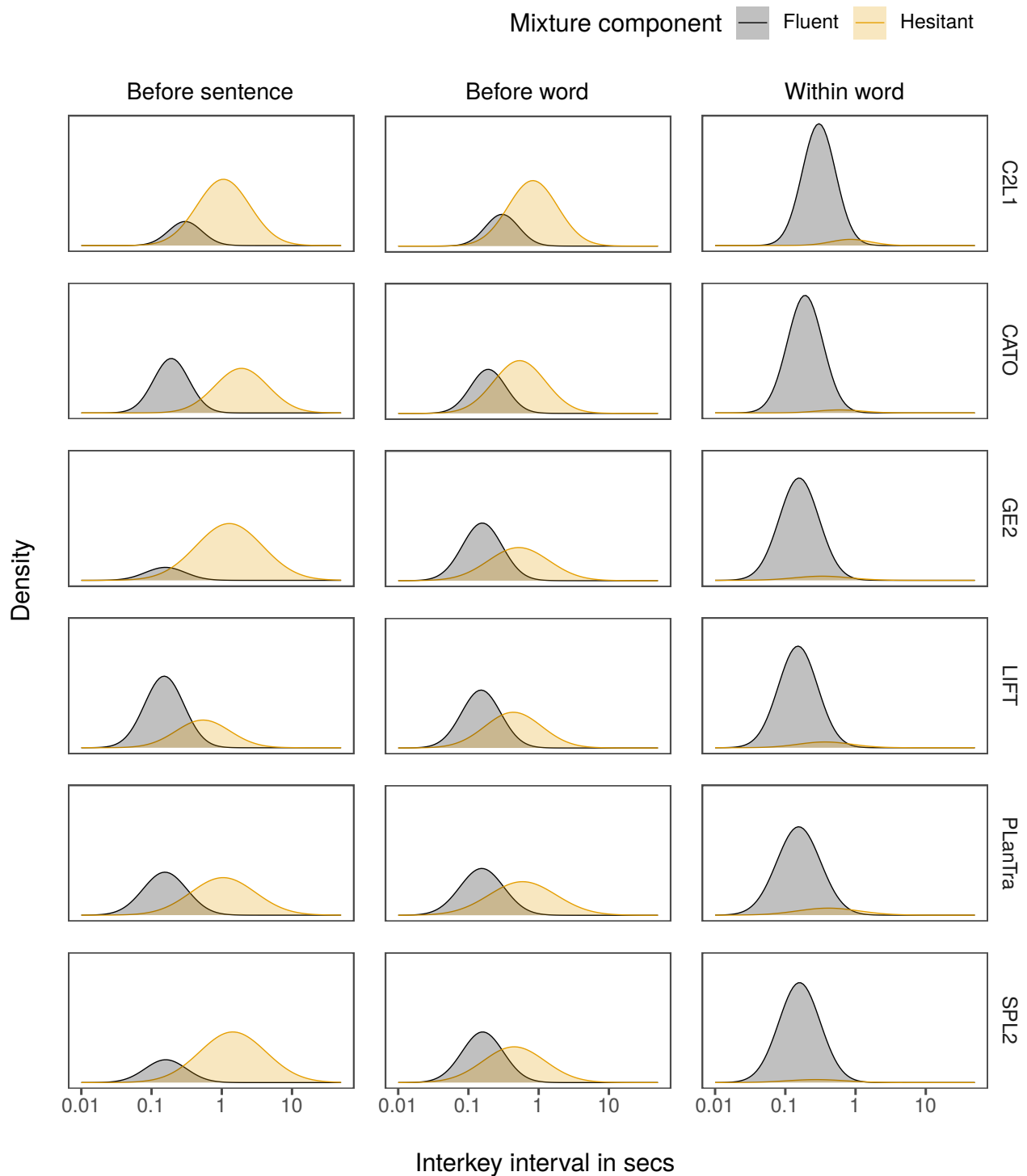
Figure 1

Mixture model plot for each transition location. Shown are the distributions for both mixture components (fluent and hesitant interkey intervals) and their weighting. Interkey intervals are shown in seconds on log scaled intervals.
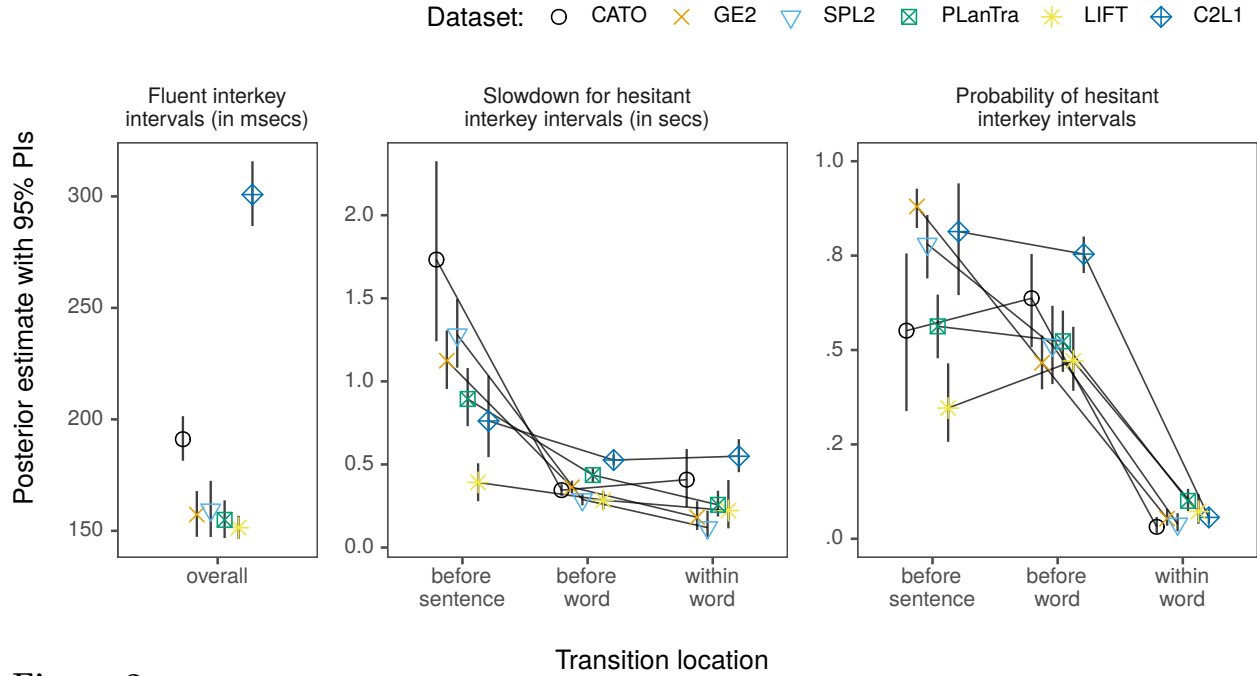
Figure 2

Mixture model parameter estimates across studies. Distributions of parameter estimates are represented as posterior mean and 95% probability interval (PI). Estimates for the CATO dataset were calculated for the non-dyslexic group, unmasked condition; also the GE2 estimtes represent the unmasked condition; SPL2 estimates are for the L1 group.

durations were longer (GE2: BF = 27; PLanTra: BF = 56; SPL2: BF = 9.1; negligible evidence for C2L1: BF = 0.1; CATO: BF = 0.2; LIFT: BF = 0.4). Hesitations were equally likely before sentences and words (C2L1 and CATO: BFs = 0.7; PLanTra: BF = 0.3; LIFT: BF = 1.6; except for GE2 and SPL2; both BFs > 100) but longer (all BFs > 100, except for C2L1: BF = 1.11 and LIFT = 0.5). Full results and parameter estimates can be found in Appendix .

Table 6

BFs for the effect of transition location on interkey intervals shown for the hesitation slowdown and hesitation probability. Comparisons for the CATO dataset were calculated for the non-dyslexic group, unmasked condition; also the GE2 estimtes represent the unmasked condition; SPL2 estimates are for the L1 group.

	Hesitation slowdown		Hesitation probability	
Dataset	before sentence vs word	before vs within word	before sentence vs word	before vs within word
C2L1	1.11	0.07	0.68	> 100
CATO	> 100	0.2	0.67	> 100
GE2	> 100	26.78	> 100	> 100
LIFT	0.5	0.41	1.61	> 100
PLanTra	> 100	55.53	0.28	> 100
SPL2	> 100	9.07	> 100	> 100

Note. BF = evidence in favour of the alternative hypothesis over the null hypothesis.

To reiterate, for most datasets we found that pauses before sentences are longer but not always more likely than before words (except for SPL2 and GE2). In fact, LIFT showed some indication that pauses were less likely before sentences than words. This is interesting because it is generally believed that pausing behaviour is associated with linguistic boundaries such that more and longer pauses are predicted for interkey intervals at larger linguistic edges (see Introduction section). It is less clear in which contexts pre-sentence pausing is more likely than pausing before words.

Differences between datasets could, to some extent, be explained by the fact that two

datasets (PLanTra, LIFT) defined before-sentence transitions as the sum of transitions between space, shift and the sentence-initial character, while the remaining data sets measured before-sentence transitions as the interval between space key and shift. To test to what extent complex key combinations affects the parameter estimates, we addressed this possibility for the SPL2 dataset and showed that including the character following the shift key substantially increased the hesitation probability for sentence-initial transitions (BFs > 100) but it did not affect the duration hesitant interkey intervals (BFs < 0.3); see Appendix C. This conflicts with the earlier finding that before-sentence hesitations were not more likely than before-word hesitations for datasets that did include the character following shift (PLanTra, LIFT). In other words, patterns in our results cannot be explained on the basis of how sentence-initial key transitions were operationalised.

Finally, Figure 2 highlights that fluent interkey intervals in two datasets (C2L1, CATO) were substantially longer than for other datasets. This is presumably reflecting that these data were sampled from the youngest and least experienced population of writers in our data pool. Interestingly, however, hesitation duration and hesitation probability followed the same patterns as the majority of datasets.

Discussion

The classical serial view (Flower & Hayes, 1980) characterises composing spontaneous multi-sentence text as a sequence of planning and execution cycles. Text is therefore produced as a series of production bursts bounded by pauses. The parallel model of writing, in contrast, sees planning, at least in competent writers, as occurring to a large extent in parallel with output (Olive, 2014). The implication of this for observation of writing timecourse – of inter-key intervals as writers compose text – is the pause duration doesn't necessarily correlated with planning necessary for next output. We implemented these two views in Bayesian statistical models, hierarchical single-distribution models capturing the serial view, and a two-distribution mixture model capturing predictions about patterning of

interkey intervals under the assumption of semi-parallel upstream processing. Fitting these models with six sets of keystroke data from free text production tasks – with a total of 953 participants producing 5,223,280 interkey intervals – we have found compelling and consistent statistical evidence in favour of the parallel view. In all cases, the predictive performance of the two-distribution mixture-models (consistent with the parallel view of writing) outperformed the single-distribution models.

The two distribution model assumes two data generating processes, one associated with the immediate demands of motor planning required for the production of a keystroke, and one that captures all upstream processing from message to abstract letter representation. A direct implication of parallel, cascaded processing is that the distribution over interkey intervals is not additive – it is not a combination of time to motor plan plus time for upstream processing. The interval between keypresses is *either* determined by motor execution *or* by processing that occurred upstream of motor execution (in cases where provision of output from the upstream processes lags behind the rate at which it can be output by the fingers). Under a serial account – where all planning necessary for production of next-text occurs in the interkey interval immediately before output of – interkey interval will be the sum of times for each processing step required for generation of that text. Both accounts predict longer mean interkey intervals at higher-order text edges (interkey intervals greater before sentences than before mid-sentence words, and before mid-sentence words than before mid-word characters). This has been consistently observed in a number of previous studies (Deane & Zhang, 2015; Mohsen, 2021; Spelman Miller, 2006; Spelman Miller et al., 2008; Torrance, Rønneberg, et al., 2016; Wengelin, 2002; Xu & Qi, 2017). However, the serial account does not permit the possibility of a distribution of short interkey intervals at higher-order edges: It strongly predicts that *all* sentence boundaries will be associated with interkey intervals that are longer than those required just for the motor planning of the next character. Under the parallel-processing account it is very likely that some – perhaps a large majority – of interkey intervals before sentences will be longer.

However there will be a distinct subset that is drawn from a distribution associated just with interkey intervals necessary for motor execution.

This is what we found. At all linguistic edges we found a distribution of interkey intervals with durations that, in previous research, have been attributed just to motor execution (refs). For mid-word interkey intervals, as might be expected, the mixture model predicted that the vast majority of interkey intervals fall within this distribution. Across the six datasets that we sampled, the central tendency for the duration of mid-word interkey intervals was broadly similar to mean mid-word interkey intervals observed in previous studies. Importantly, however, these short interkey intervals were also present at higher-order text edges. Across all datasets we found, at minimum, a non-trivial minority of sentence-initial interkey intervals were sampled from the short distribution (i.e. with durations that could only be associated with motor execution). In two cases – for adult writers sampled in the PLanTra and Lift datasets – the majority of interkey intervals fell within this distribution. Thus, although as might be expected there was a considerably increased tendency for longer interkey intervals at higher order boundaries: Planning associated with planning a new sentence is, probabilistically, much more likely to spill beyond output of the previous sentence and therefore affect duration of the sentence-initial interkey interval. However the presence of a non-trivial proportion of interkey intervals with a duration that is inconsistent with anything other than motor execution can only be explained with recourse to theories that permit preparation in parallel with preceding output.

Our results showed that the hesitation probabilities are largely identical before sentences and before words, which suggests that writers frequently plan the next word and even sentence in parallel to production – consistent with the parallel view of writing – which mitigates the need to pause to plan up-coming linguistic information.

This parallelism was evident even in the youngest writers in our data pool (C2L1; mean age: 11.8 years). As might be expected for children who compose predominantly by

handwriting and whose typing skills will still be developing, motor execution rate (mean duration of fluent transitions) was substantially slower compared to the more experienced typists in other datasets. In all other respects, however, findings for this dataset were similar to that of other datasets and consistent with parallel processing. A two-distribution mixture model provided best fit to these data. At both before-word and before-sentence locations a non-trivial number of interkey intervals were within the short distribution - i.e. at durations too short to permit lexical retrieval or syntactic planning. Probability of longer intervals was greater before-sentence and before-word transitions compared to mid-word transitions. This is interesting because, for example, Olive (2014) described a parallel model that operates in a serial fashion for inexperienced or struggling writers, explained on the basis of task demands that reduce the ability to plan in parallel to processing which leads to a serialisation of planning units. However, the results presented in this paper suggest that pausing behaviour in young writers largely mirror results from more experienced writers: Pauses were both equally long and likely at before-word and before-sentence transitions but more likely compared to mid-word transitions. Also for L2 writers (PLanTra) we observe pausing patterns that do not resemble a serialised writing process as evidenced by a large number of fluent transitions at word and sentence boundaries.

We observed two more differences across datasets – other than the patterns summarised above for C2L1 – that are worth highlighting. Both can largely be explained on the basis of differences associated with the population (writing competence / experience) that these samples were obtained from and text genre they were asked to produce (see also Conijn et al., 2019): The first exception concern the GE2 and SPL2 datasets: pauses were more likely to occur before sentences than before words; this difference was absent in the remaining data sets. **TODO: I don't have an explanation for this.** Second, pauses at before-sentence locations were not always longer than before words or mid-word; specifically there were two exceptions: (1) sentence-initial hesitations were not longer than word-initial hesitation for the C2L1 dataset possibly because these sample of young inexperienced writers

tend to use a more localised word-level planning strategy for text production. (2) pause durations did not vary across transition locations in the LIFT dataset. The absence of a difference could be explained as specific to the writing task because, in synthesis, there is less need for planning content and text structure: the structure is often kept similar to the source in synthesis writing ("structural isomorphism"', Hidi & Anderson, 1986). However, the results of the PLanTra dataset rule out this possibility: there was evidence for longer hesitations at larger linguistic edges for a text simplification task that also does not require planning of contents or generating new sentence structures.

An observation that was not strictly predicted by the parallel view is that the unconstrained mixture model M5 that allowed the distribution over durations of fluent transitions to vary between transition locations showed a higher predictive performance. This can be explained on the basis of low-level keyboarding activity: It is possible that letter bigrams are systematically produced faster than transitions between space and a subsequent letter – as in before-word transitions – or shift – at before sentence locations. This is for two reasons: first, and importantly, highly frequent bi- and even trigrams may be stored, retrieved and executed as one motor code (Behmer Jr. & Crump, 2016; Grudin & Larochelle, 1982; Ostry, 1983; Terzuolo & Viviani, 1980) because of the strong association between letters. This association reduces the length of transition durations. It is less likely that the same association exists for space-letter and space-shift pairs. Second, in two datasets (PLanTra, LIFT) before-sentence transitions are the sum of the transitions between space, shift and the following character key and therefore necessarily longer than other transitions. We found no evidence for the latter possibility (see Results section and Appendix C).

A possible concern with our result – that two-distributions mixture models showed substantially better predictive performance – is that as mixture models have more parameters they might always outperform single-distribution models. This concern was preempted by using cross-validation techniques for model comparison which is preventing

model overfit. In addition we used a simulation approach to compare a single distribution model and a two distributions mixture model. We simulated two datasets that were either based on a single distribution data-generating process or a process with a two-distributions process. This approach allows us to test the predictive performance of models in a context where we know the true underlying data generating process – a single distribution vs a mixture of two distributions – and we can test to what extent these models can successfully uncover the true parameter values. Importantly, we can test the performance of a mixture model for data that come from a single process. Modelling details can be found in Appendix J. As might be expected, we found that the two-distribution mixture model was successful at uncovering the parameter values of the data generated with a two-distributions mixture process; we observed the same for the single-distribution model applied to the data generated with a single distribution process. Parameters were not successfully uncovered when we switched model type and dataset. Importantly though, cross-validation rendered a substantially higher predictive performance for the mixture model compared to the single-distribution model for data simulated from a two-distributions mixture process, but not when applied to data based on a single-distribution process. Therefore we can rule out the possibility that the statistical support for the two-distributions mixture-models can be explained on the basis of their larger number of parameters (i.e.model overfitting).

Throughout this paper we assumed that hesitations reflect mental planning of upcoming ideas and encoding of linguistic units. Alternatively, at least some if not all pauses in the writing process might be the result of reading or looking back into previously produced text. There is limited research that used eye tracking to investigate regressive gaze behaviour during writing (Alamargot et al., 2010; Beers et al., 2010; Chukharev-Hudilainen et al., 2019; De Smet et al., 2018; Torrance et al., n.d.; Van Waes et al., 2010). There are at least four reasons why eye movements away from the inscription point might occur during writing: First, reading is necessary for revision (i.e. writers must check if writing goals have been met). Second, writers might look for or correct spelling or grammatical errors. We

removed transitions that terminated in an editing operation so the pauses we detected are unlikely to reflect revisions of the previous produced text. Third, writers might look at the source they are writing from. For two datasets (PLanTra, LIFT) which involved writing from sources, we removed transitions that were made when the source (rather than the writing document) was in focus.[7] Fourth, writers might use text to cue or reinstate ideas after interruption of the writing process (Hayes, 1996; Johansson et al., 2010).

As for the fourth reason for why writers might look back in their text: frequencies of lookbacks during writing follow a similar pattern as the one we observed for pausing: for example Torrance, Johansson, et al. (2016) reported that lookbacks appear with a frequency of 45% before sentences, 12% before words and 5% within words of which 36% were associated with sustained reading but mostly less patterned forward and backward saccades between words ("hopping," see also Chukharev-Hudilainen et al., 2019). In contrast to this observation – that lookbacks are more frequent before sentences compared to words – we found that pauses appear equally often before sentences and words under our two-distributions mixture-model. Finally, even though reading is likely to explain some proportion of our results, lookbacks in previously written text are overall rare, certainly in samples of university students (Chukharev-Hudilainen et al., 2019; Torrance, Johansson, et al., 2016). Also, pause frequency did not change when the produced text was masked (see comparisons for the CATO and GE2 data in Appendix E), and therefore if reading previously produced text was not possible.

A practical advantage of the mixture-model approach (also Roeser et al., 2021) is that we are not required to stipulate interval thresholds as plausible candidates for lower pause bound to handle the complex distribution of latency from spontaneous text production. Such thresholds are widely used by writing researchers, a strategy that was

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[7] As for PlanTra, most participants copy-pasted the source text into their word log. In other words, pauses might to some extent result from reading the source text.

inherited from early research in speech production (for review see Rochester, 1973), with studies dating back to at least the mid 1990s (Foulin, 1998). There is one central problems with this approach: A threshold requires a definition of what passes as a pause (Van Waes et al., 2016; Wengelin, 2006), i.e. a pause criterion threshold often set to 2 secs (Chanquoy et al., 1996; Kaufer et al., 1986; Sullivan & Lindgren, 2002; Wengelin, 2002) or some other lower bound (Chukharev-Hudilainen, 2014; Connelly et al., 2012; Leijten & Van Waes, 2013). Even if these thresholds were adjusted relative to factors such as writing medium, experience of writer, and text location of pause (see e.g. Wengelin, 2006) they would be arbitrary. For example, a sentence-initial pause of 2 secs has a very different interpretation from a 2 secs pause that occurs before or within a word. Our current understanding of the processes that underlie text production does not provide a strong theoretical basis on which to make this decision. So while a 2 secs threshold undoubtedly captures an interesting distinction – processing that occurs in the range zero to 2 secs is very likely to be qualitatively different from processing that takes more than 2 secs. However the same could be argued for any threshold between perhaps 250 msecs and 10 secs that a researcher might care to choose (Chenu et al., 2014). Mixture models provide a principled statistical framework that allows the researcher to model behavioural data that come from a combination of cognitive processes without imposing threshold values (see also Almond et al., 2012; Baaijen et al., 2012; Hall et al., 2022; Li, 2021).

Conclusion

In contrast to the serial pause-and-burst view, the parallel view emphasises that writers do not necessarily pause to plan the upcoming language unit but plan in parallel to writing execution. Using the Bayesian framework we implemented models of both the serial model of writing and the parallel view. Model comparisons and the inspection of posterior parameter estimates support the parallel view of writing but provide strong evidence against the serial view. We found that interkey intervals across word and even sentence boundaries are frequently fluent and not interrupted but planning of upcoming linguistic information.

This pattern was found to be largely consistent for populations with different levels of writing experience and languages (e.g. young / L2 writers, students) and writing tasks (e.g. essays, syntheses).

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Appendix A

Statistical models

We used the Bayesian framework (e.g. Farrell & Lewandowsky, 2018; Gelman et al., 2014; Lee & Wagenmakers, 2014) to implement four statistical models to evaluate which – the serial or the parallel view – captures interkey data more successfully. In other words, we use statistical models to map between the keystroke intervals and the theoretically assumed process that generates theses data to then compare the predictive power of those models. These models presented in this section are building on one another so that later models include assumptions of earlier models.

Single-distribution Gaussian

Under the serial view, all planning must be completed prior to typing onset of the corresponding planning unit. The resulting interkey interval is sometimes faster or slower depending on, among others, psycholinguistic factors; i.e. the interval before a word is shorter for easily retrievable high-frequency words, or longer for low frequency words, shorter for words with fewer graphemes, syllables, and morphemes. For example, we can capture the variability associated with word-features by assuming that before-word interkey intervals can be described as coming from a distribution that is normal (Gaussian) with two parameters, an unknown mean μ, that describes the average interkey interval associated with word-level planning, and a standard deviation σ_{e}^2, that captures the remaining variability associated with factors that we did not further specify in the model. This can be expressed as $\mathrm{iki}_{\mathrm{before\ word}} \sim \log\mathcal{N}(\mu, \sigma_{\mathrm{e}}^2)$ where $\mathrm{iki}_{\mathrm{before\ word}}$ are all interkey intervals immediately proceeding a word. Of importance is the estimated posterior value of μ as this value captures average time needed to mentally prepare a word.

We can extend this simple model of word-planning to other linguistic location. Larger linguistic edges are typically understood as being associated with planning on higher levels. For example, at sentence boundaries, planning needs to happen for word-level properties –

which we captured before as average interkey interval μ – but also higher linguistic planning such as clause-level meaning, and dependencies of the sentence-initial noun (Nottbusch et al., 2007; Roeser et al., 2019). Using regression formulae we can capture changes in the outcome variable that are associated with other factors. More specifically we can decompose μ as $\mu = \alpha + \beta \cdot \text{x}_{\text{sentence}[0,1]}$ so that when $\text{x}_{\text{sentence}}$ takes on the value 0, the equation reduces to $\mu = \alpha$ which is then the average interkey interval for word boundaries but, when $\text{x}_{\text{sentence}}$ takes on the value 1, the average interkey interval for word boundaries α is incremented by a slowdown associated with sentence boundaries of β msecs. Therefore the value of the β parameter represents the additional cognitive demand associated with sentence-initial planning. The application of such a statistical model to the data will therefore provide us with an estimate of the parameter value that can be used for statistical inference (e.g. whether there is a statistically meaningful difference associated with word and sentence boundaries).

We implemented the average interkey interval associated with a given text locations as β_{location} in equation A1 where location is taking on an index for each transition location. Therefore, the model returns three distributions of β values that capture the posterior distribution of average interkey intervals for each transition location. The decomposition of μ allows us to address the fact that some writers are faster than other writers by introducing a parameter for what is called random intercepts $u_{\text{participant}}$. The random intercepts term $u_{\text{participant}}$ is constrained so that the value it takes on comes from a normal distribution with a mean of 0 and a standard deviation of σ_{p}^2. The $u_{\text{participant}}$ value is therefore the difference between the overall posterior estimate and estimate average interkey interval of a particular participant (i.e. a positive value indicates that a participant is slower than average; a negative value indicates that a participant is faster than average).

The resulting model is shown in equation A1 and represents a Gaussian mixed-effects model

$$\text{iki}_i \sim \ \log\mathcal{N}(\mu_i, \sigma_{\text{e}}^2)$$

$$\text{where: } \mu_i = \beta_{\text{location[i]}} + u_{\text{participant[i]}}$$

$$u_{\text{participant[i]}} \sim \mathrm{N}(0, \sigma_{\text{p}}^2)$$

$$\text{constraint: } \sigma_{\text{e}}^2, \sigma_{\text{p}}^2 > 0$$

(A1)

where i iterates over every interkey interval $i \in 1 \dots N$ with N being the total number of interkey intervals; thus location[i] is the transition location associated with the iˆth keystroke and participant[i] is the participant associated with the iˆth keystroke.

Standard-deviation parameters were constrained to be positive because standard deviations can never be negative.

Single distribution log-Gaussian

The previous model assumes that the data-generating process follows a Gaussian distribution. As a consequence the Gaussian model generates values that are symmetrically distributed and, in principle, allows values to be negative. The model presented in this section is largely identical to the previous model but instead of assuming a Gaussian, we assume that the data come from a log-normal (log-Gaussian) distribution.

There are, at least, two arguments for using a log-Gaussian distribution: (1) log-Gaussians are zero-bound; in contrast to Gaussians, a log-Gaussian does not allow negative values. This is a desirable property because the distance between two subsequent key events must be positive. Instead the lower bound is delimited by a person's ability to move their fingers and keyboard polling. (2) the log-scale is known to be a better match for data from human behaviour and motor responses. In particular, a Gaussian distribution assumes that units are scaled linearly. For example, a difference of 25 msecs is the same between 100 and 125 msecs as between 5 secs and 5,025 msecs. This does not map onto the psychological interpretation for short and long interkey intervals. For example effects that

result from the motor level within words (e.g. typing a high vs a low frequency bigram) are smaller than differences that are due to high levels of processing (retrieving a word in an L1 or L2). In other words, an effect of 25 msecs can be large in the context of fast inerkey intervals but it is small in the context of overall slow intervals. Log-Gaussian distributions are a natural way of translating a linear scale to an exponential scale so that a 25 msecs difference on the lower end of interkey intervals (motor activity) is more psychologically meaningful than a 25 msecs difference on the upper end (retrieving words, planning sentences).

This model can be described as in equation A2 in which the distribution $\log\mathcal{N}()$ was replaced by $\log\mathcal{N}()$.

$$
\begin{aligned}
\text{iki}_i &\sim \log\mathcal{N}(\mu_i, \sigma_{\text{e}}^2) \\
\text{where: } \mu_i &= \beta_{\text{location[i]}} + u_{\text{participant[i]}} \\
u_{\text{participant[i]}} &\sim \mathcal{N}(0, \sigma_{\text{p}}^2) \\
\text{constraint: } \sigma_{\text{e}}^2&, \sigma_{\text{p}}^2 > 0
\end{aligned}
\tag{A2}
$$

Single distribution unequal-variance log-Gaussian

The third model is identical to the model presented in the previous section but removed the equal-variance assumption for the width of the distributions assocated with transition locations. The previous models modelled interkey intervals as a function of transition location meaning that the average interkey interval depends on its position in the text. The variance associated with the estimated interkey intervals for each transition location was assumed to be identical (equal variance). This assumption is however not in line with what we know about data from human motor behaviour. Longer latencies are known to be associated with a larger variances for both response-time data in particular (Wagenmakers & Brown, 2007) and human motor behaviour in general (Schöner, 2002; Wing & Kristofferson, 1973). For interkey intervals pauses at larger linguistic edges can therefore

be assumed to be associated with a larger variance also because of the larger number of associated processes. Therefore, in equation A3, we introduced the assumption that standard deviations $\sigma^2_{e_{\text{location}}})$ vary by transition location.

$$
\begin{aligned}
\text{iki}_i &\sim \ \log\mathcal{N}(\mu_i, \sigma^2_{e_{\text{location[i]}}}) \\
\text{where: } \mu_i &= \beta_{\text{location[i]}} + u_{\text{participant[i]}} \\
u_{\text{participant[i]}} &\sim \mathcal{N}(0, \sigma^2_{\text{p}}) \\
\text{constraint: } \sigma^2_{\text{e}}&, \sigma^2_{\text{p}} > 0
\end{aligned}
\tag{A3}
$$

Two-distributions log-Gaussian mixture model

The following model is an extension of the last single-distribution model. In contrast to the models introduced for the serial view, the cascading view allows planning to unfold in parallel to production. Therefore, we removed for the model presented in this section the constraint that all planning must be completed before writing onset. Instead of assuming that larger linguistic edges shift the distribution of interkey intervals as in the previous models, we modelled pauses in the distribution of interkey intervals, under the parallel view, to be more likely to occur at larger linguistic edges. This was achieved by introducing the model assumption that interkey intervals come from a weighted combination (mixture) of two distributions associated with two different states:

1. Activation can flow into keystrokes without interruption. These fluent keystroke transitions are merely constrained by a person's ability to move their finger and were captured by β in equation A4. Note that β is represented in both log-Gaussian distributions in equation A4 referring to the same unknown parameter.

2. Interruptions in the activation flow from higher to lower levels result in longer keystroke intervals, when information, for example words or their spelling, could not be retrieved in time. The slowdown for these hesitant transitions is captured by δ in the

first line of equation A4 which represents the magnitude of the slowdown associated with transition location. The slowdown δ was allowed to vary by transition locations because hesitations at larger linguistic units are likely to be associated with higher level planning which causes longer delays in the output. The δ parameter was constrained to be positive, so that it captures how much longer hesitant interkey intervals are in addition to β.

$$
\begin{aligned}
\text{iki}_i \sim\ & \theta_{\text{location[i], participant[i]}} \times \log\mathcal{N}(\beta + \delta_{\text{location[i]}} + u_{\text{participant[i]}}, \sigma^2_{e'_{\text{location[i]}}}) + \\
& (1 - \theta_{\text{location[i], participant[i]}}) \times \log\mathcal{N}(\beta + u_{\text{participant[i]}}, \sigma^2_{e_{\text{location[i]}}}) \\
\text{where:}\ & u_{\text{participant[i]}} \sim \mathcal{N}(0, \sigma^2_{\text{p}}) \\
\text{constraint:}\ & \delta, \sigma^2_e, \sigma^2_{e'}, \sigma^2_{\text{p}} > 0 \\
& \sigma^2_{e'} > \sigma^2_e \\
& 0 < \theta < 1
\end{aligned}
\tag{A4}
$$

The first line of equation A4 represents the distribution of hesitant interkey intervals; the second line represents fluent interkey intervals. Each of these two distributions is associated with the mixing weight θ which is a proportion that is constrained to be larger than 0 and smaller than 1. θ is here parameterised to represent the probability that an interkey interval is associated with the distribution of long interkey intervals, hence representing the hesitation probability. This probability is inversely related to the mixing weight of the distribution of short interkey intervals by $1 - \theta$ because the weights of both distributions must sum to 1. In other words, a larger weight for one distribution inevitably means a lower weight for the other distribution.

The probability of hesitant transitions is assumed to vary as a function of both transition location and participants. In line with the literature discussed in the introduction, we assumed that pauses are likely to vary across linguistic edges. As pausing is subject to

individual differences and writing style (skills), we also assumed that some participants pause more at certain transition locations and other participants pause less.

Lastly, we carried over the unequal variance assumption and let the standard deviations $\sigma_{e'}^2$ and σ_e^2 vary by transition location. In addition we constrained the variances so that $\sigma_{e'}$ associated with the distribution of typing hesitations is larger than the variance associated with fluent transitions σ_e (see Vasishth, Chopin, et al., 2017; Vasishth, Jäger, et al., 2017).

Appendix B

Fit to data

Model fit was assessed by testing to what extent simulations obtained from the model fit the observed data. From each model we obtained 50 simulations (predictions); see Figure B1. The model predictions fitted the data substantially better for the mixture models. The worse fit was observed for the single distribution Gaussian model which predicted a larger number of negative keystroke intervals; a log-normal distribution removed these negative predictions.
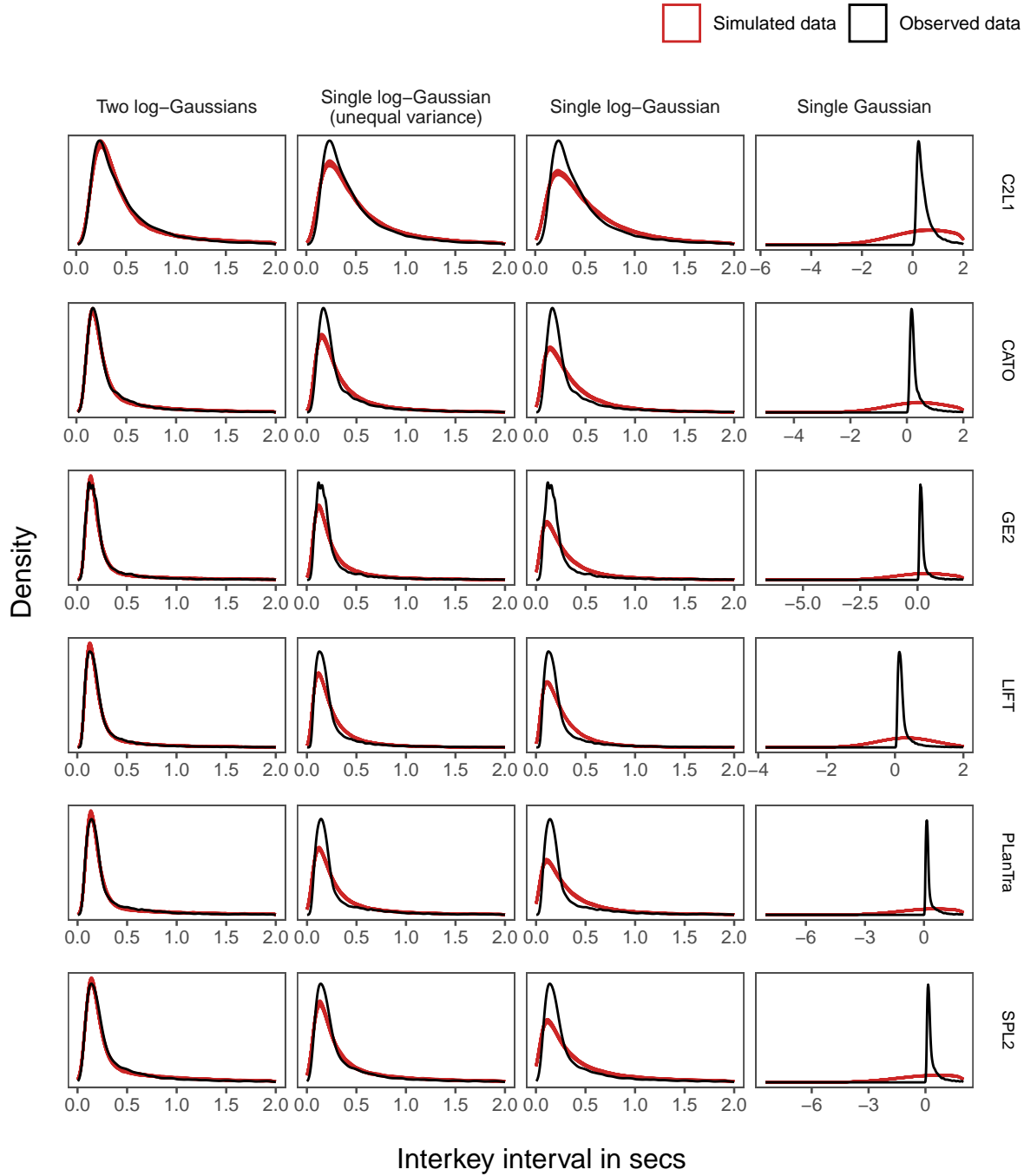
Figure B1

Predicted data (50 simulations in each cell) in red in comparison to the interkey interval data shown in black by model types and datasets. Model fit to the data was order from the best (left) to the weakest (right). For illustration the x-axis was truncated at 2 secs.

Appendix C

Key-combination effect

The analysed datasets differ to the extent that interkey intervals at before sentence location did (PLanTra, LIFT) or did not (CATO, C2L1, SPL2, GE2) scope over both the transition to the shift key and the the transition to the character following the shift key. In other words, the pause before sentences summed across two key intervals in the PLanTra and LIFT data, namely `_^[shift]^C`, where ^ represents a transition between keys, but only one key interval, namely `_^[shift]`, for the remaining datasets. Therefore, longer or more frequent pauses for transitions immediately proceeding a sentence could be explained without reference to linguistic edges.

Therefore we compared whether any difference can be explain on the basis of the additional keystroke involved in before-sentence transitions. We used the SPL2 data for this comparison and calculated intervals including and excluding the keystroke after shift. Although we modelled all transition locations, we present only before-sentence transitions below as there was, as one would expect, no difference for before and within-word key-intervals. The results of this comparison can be found in Table C1 (only for the data from participants writing in their first language).

Table C1

Mixture model estimates for interkey interval immediately preceding a sentence. Cell means are shown for interkey intervals that do and do not involve the interkey intervals to the character following shift in msecs for the slowdown and the probability of hesitant interkey intervals. The difference for including the interkey intervals to the character after shift is shown on log scale (for durations) and logit scale for probability of hesitant interkey intervals; 95% PIs are shown in brackets.

Model parameter	_^[shift]^C	_^[shift]	Difference	BF
Fluent interkey intervals	156 [145, 169]	159 [147, 172]	-0.02 [-0.13, 0.09]	0.06
Hesitation slowdown	1,167 [1,037, 1,305]	1,281 [1,082, 1,496]	-0.06 [-0.21, 0.09]	0.11
Hesitation probability	1.00 [.99, 1.00]	.78 [.69, .86]	4.91 [3.68, 6.35]	> 100

Note. PIs are probability intervals. BF is the evidence in favour of the alternative hypothesis over the null hypothesis.

The duration of fluent and hesitant interkey intervals was not affected by whether or not the sentence-initial transition include the character following shift. However, we found strong evidence for an increased hesitation probability when the before-sentence key transition included the character following the shift key. Notably, the hesitation probability increased closes to ceiling when the transition following the shift key was added. In other words the mixture model identifies almost all before-sentence transition as being hesitant as they always include two keystrokes while interkey intervals from all other transition location – the majority of the data – do not.

Appendix D

L2 effect (SPL2)

For the SPL2 data we calculated the L2 effect (i.e. the difference between writing in L2 and L1). The results can be found in Table D1. The results show longer hesitation duration and more pauses across all transition locations when writing in L2. Only within-word transitions did show negligible evidence for an increased hesitation duration in L2.

Table D1

Mixture model estimates for language effect. Cell means are shown the slowdown for hesitant interkey intervals when writing in L1 and L2 and the probability of hesitant keyintervals. The language difference is shown on log scale (for durations) and logit scale for probability of hesitant key intervals. 95% PIs in brackets.

Transition location	L1	L2	Difference	BF
Hesitation showdown				
before sentence	1,281 [1,082, 1,496]	1,802 [1,557, 2,073]	0.31 [0.17, 0.45]	> 100
before word	289 [254, 327]	560 [507, 617]	0.47 [0.39, 0.55]	> 100
within word	120 [53, 222]	202 [156, 258]	0.27 [-0.07, 0.55]	0.68
Hesitation probability				
before sentence	.78 [.69, .86]	.92 [.87, .96]	1.23 [0.52, 1.97]	> 100
before word	.51 [.41, .62]	.89 [.83, .93]	2.02 [1.4, 2.66]	> 100
within word	.04 [.02, .07]	.15 [.10, .22]	1.52 [0.78, 2.29]	> 100

Note. PIs are probability intervals. BF is the evidence in favour of the alternative hypothesis over the null hypothesis.

Appendix E

Masking effect (CATO, GE2)

Studies associated with two datasets (CATO, GE2) investigated to what extent masking the previously written text affects keystroke behaviour. The mixture model results for the effect of masking is shown in Table E1. There was some evidence for longer before-sentence hesitation durations when the text was masked in non-dyslexic writers. Evidence for all other comparisons was negligible.

Table E1

Mixture model estimates for masking effect. Cell means are shown for the masked and unmasked writing task for the slowdown (in msecs) and the probability of hesitant transitions. The effect for masking is shown on log scale (for durations) and logit scale for probability of hesitant transitions. 95% PIs in brackets.

| Transition location	Dataset	Group	Unmasked	Masked	Difference	BF
Hesitation slowdown						
before sentence	CATO	dyslexic	2,231 [1,543, 3,111]	1,680 [1,239, 2,205]	-0.25 [-0.64, 0.13]	0.44
before sentence	CATO	non dyslexic	1,733 [1,241, 2,325]	1,502 [1,134, 1,942]	-0.12 [-0.47, 0.22]	0.23
before sentence	GE2	non dyslexic	1,124 [954, 1,307]	1,418 [1,218, 1,634]	0.21 [0.05, 0.36]	2.59
before word	CATO	dyslexic	444 [405, 485]	407 [369, 447]	-0.06 [-0.13, 0.01]	0.14
before word	CATO	non dyslexic	345 [312, 381]	326 [295, 361]	-0.04 [-0.11, 0.04]	0.06
before word	GE2	non dyslexic	363 [325, 403]	379 [341, 420]	0.03 [-0.05, 0.11]	0.05
within word	CATO	dyslexic	278 [166, 400]	177 [116, 252]	-0.24 [-0.52, 0.06]	0.57
within word	CATO	non dyslexic	409 [244, 593]	392 [230, 591]	-0.03 [-0.42, 0.38]	0.2
within word	GE2	non dyslexic	182 [105, 279]	209 [135, 306]	0.08 [-0.24, 0.4]	0.19
Hesitattion probability						
before sentence	CATO	dyslexic	.60 [.38, .79]	.80 [.60, .93]	0.2 [-0.06, 0.46]	0.45
before sentence	CATO	non dyslexic	.55 [.34, .76]	.68 [.47, .84]	0.13 [-0.16, 0.4]	0.21
before sentence	GE2	non dyslexic	.88 [.82, .93]	.90 [.85, .94]	0.16 [-0.46, 0.79]	0.36
before word	CATO	dyslexic	.75 [.64, .85]	.72 [.59, .82]	-0.04 [-0.19, 0.12]	0.09
before word	CATO	non dyslexic	.64 [.51, .75]	.62 [.49, .74]	-0.02 [-0.19, 0.16]	0.09

Table E1 continued

Transition location	Dataset	Group	Unmasked	Masked	Difference	BF
before word	GE2	non dyslexic	.47 [.40, .54]	.45 [.38, .52]	-0.06 [-0.46, 0.35]	0.21
within word	CATO	dyslexic	.07 [.03, .12]	.11 [.06, .19]	0.05 [-0.02, 0.13]	0.08
within word	CATO	non dyslexic	.03 [.02, .06]	.03 [.02, .06]	0 [-0.03, 0.03]	0.01
within word	GE2	non dyslexic	.05 [.03, .08]	.04 [.03, .06]	-0.29 [-0.88, 0.28]	0.48

Note. PIs are probability intervals. BF is the evidence in favour of the alternative hypothesis over the null hypothesis.

Appendix F

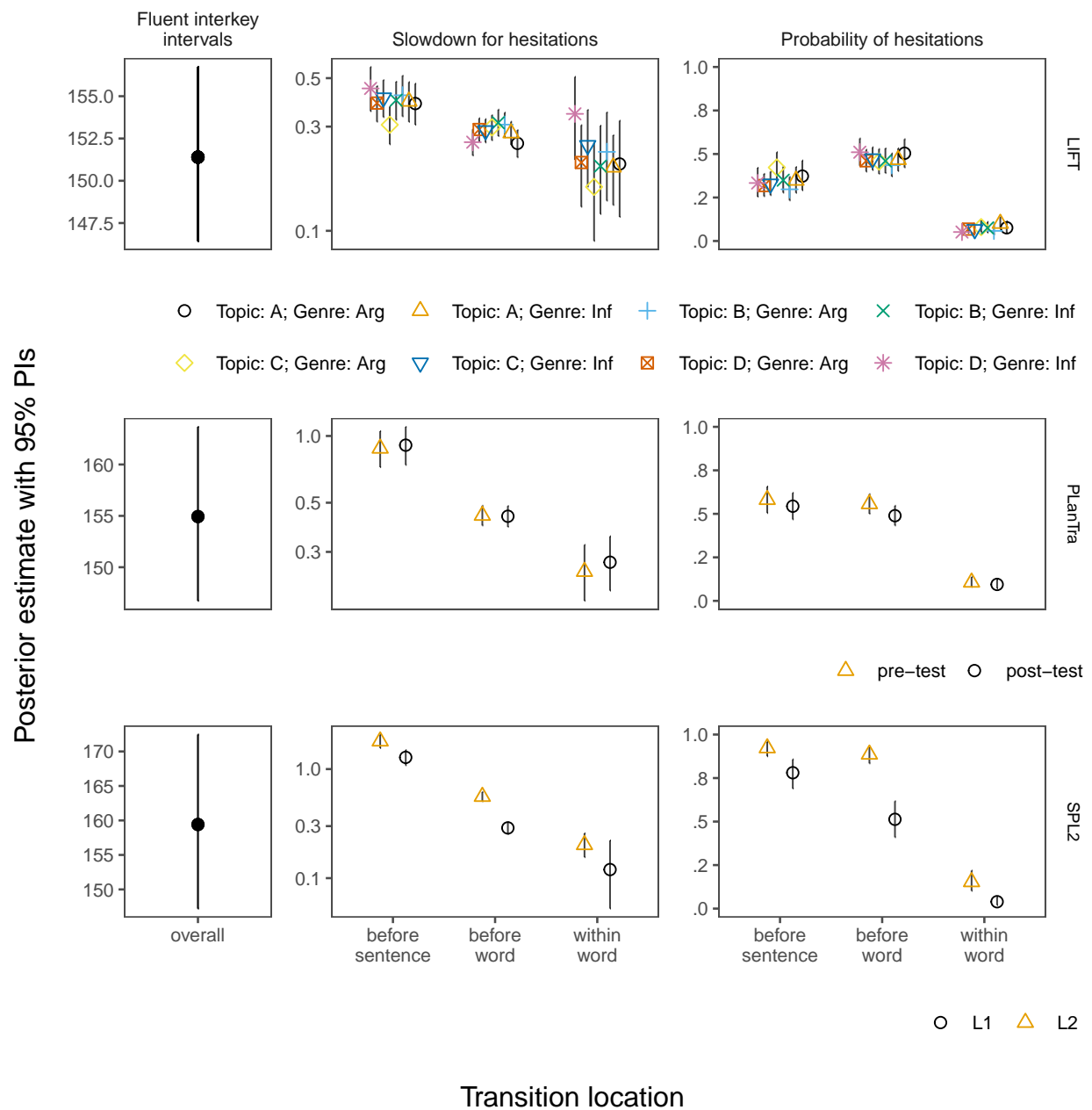**Posterior parameter estimates**
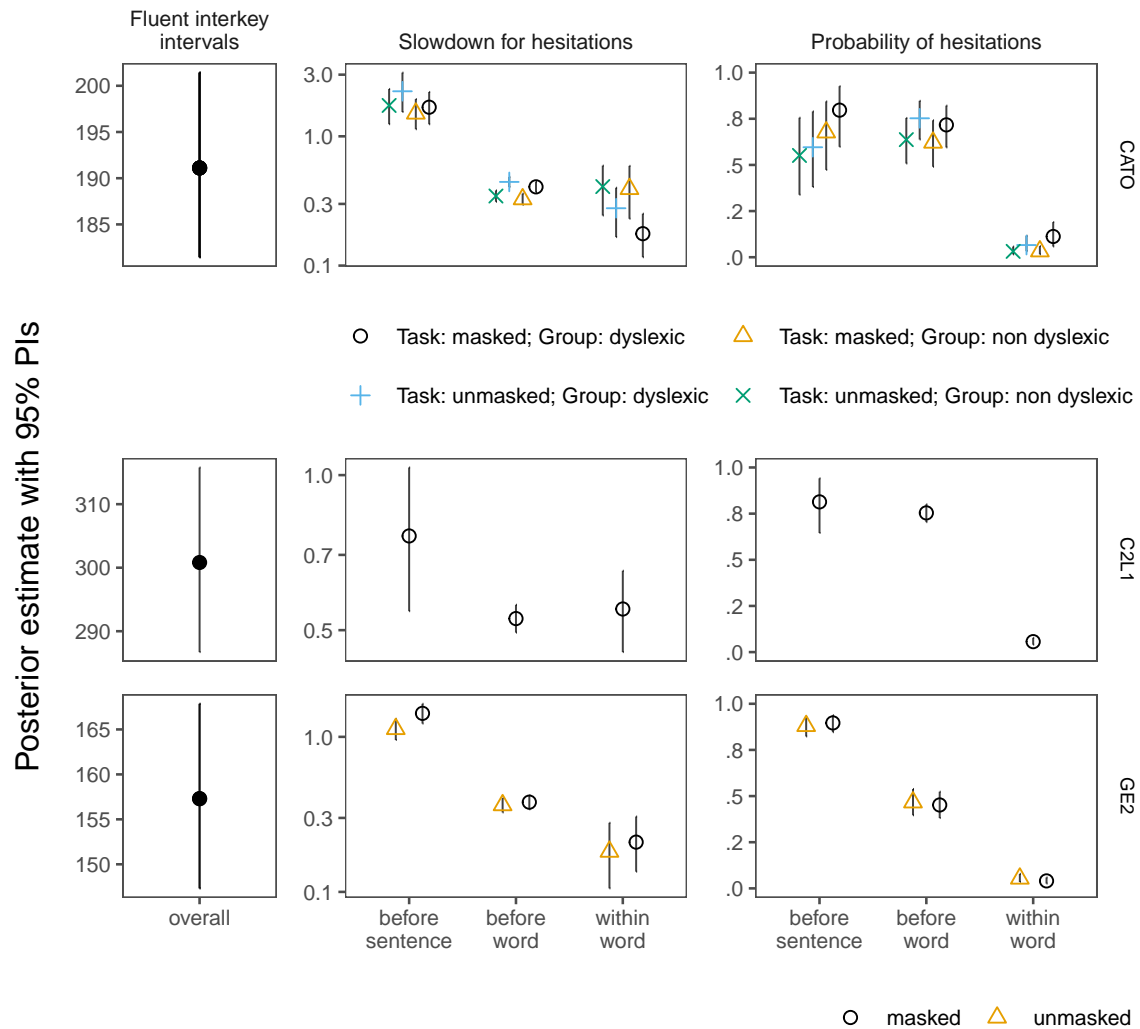
Figure F1

Distribution of posterior parameter estimates with 95% probability intervals (PI). Fluent interkey intervals are shown in msecs and the slowdown for hesitant key intervals in secs; probability of hesitations is the proportion of hesitant interkey intervals.

Figure F1 (cont.)

Distribution of posterior parameter estimates with 95% probability intervals (PI). Fluent interkey intervals are shown in msecs and the slowdown for hesitant key intervals in secs; probability of hesitations is the proportion of hesitant interkey intervals.

Appendix G

Pre-post test (PLanTra)

The pre-post test effect for the PLanTra dataset is reported in Table G1. Evidence for all comparisons was negligible.

Table G1

Mixture model estimates for post-test effect. Cell means are shown for the pre-test and post-test in msecs for the slowdown for hesitant interkey intervals (hesitation duration) and the probability of hesitant interkey intervals. The effect for post-test is shown on log scale (for interkey intervals) and logit scale for probability of hesitant interkey intervals. 95% PIs in brackets.

Transition location	Pre-test	Post-test	Difference	BF
Hesitation duration				
before sentence	879 [723, 1,052]	909 [740, 1,100]	-0.03 [-0.23, 0.17]	0.1
before word	438 [395, 485]	434 [389, 483]	0.01 [-0.08, 0.1]	0.05
within word	245 [180, 323]	269 [201, 353]	-0.06 [-0.3, 0.18]	0.14
Hesitation probability				
before sentence	.58 [.50, .66]	.54 [.47, .62]	0.15 [-0.26, 0.58]	0.27
before word	.56 [.50, .61]	.49 [.43, .55]	0.27 [-0.04, 0.59]	0.72
within word	.11 [.08, .14]	.09 [.07, .12]	0.13 [-0.27, 0.54]	0.26

Note. PIs are probability intervals. BF is the evidence in favour of the alternative hypothesis over the null hypothesis.

Appendix H

Genre effect (LIFT)

From the LIFT data, we compared the difference between genres, i.e. when writing an informative text as opposed to writing an argumentative text. The results are shown in Table H1. Cellmeans and differences were average across writing topic. Evidence for a genre comparisons was negligible.

Table H1

Mixture model estimates for genre effect. Cell means are shown for argumentative and informative texts in msecs for the hesitation slowdown and the probability of hesitant transitions. The effect for genre is shown on log scale (for transition durations) and logit scale for probability of hesitant transitions. 95% PIs in brackets.

Transition location	Argumentative	Informative	Difference	BF
Hesitation duration				
before sentence	373 [301, 454]	411 [330, 504]	-0.07 [-0.33, 0.19]	0.16
before word	287 [250, 326]	284 [248, 323]	0.01 [-0.15, 0.16]	0.09
within word	199 [118, 306]	246 [155, 361]	-0.12 [-0.6, 0.36]	0.29
Hesitation probability				
before sentence	.35 [.28, .43]	.34 [.27, .42]	0.05 [-0.57, 0.73]	0.36
before word	.46 [.39, .54]	.48 [.41, .55]	-0.05 [-0.51, 0.44]	0.25
within word	.07 [.05, .10]	.07 [.05, .10]	-0.02 [-0.81, 0.76]	0.46

Note. PIs are probability intervals. BF is the evidence in favour of the alternative hypothesis over the null hypothesis.

Appendix I

Transition location effect

Table I1

Effect of transition location on interkey intervals. Differences are shown on log scale (for durations) and logit scale for hesitation probability. 95% PIs in brackets.

	Hesitation slowdown		Hesitation probability	
Comparison	Est. [95% PIs]	BF	Est. [95% PIs]	BF
C2L1				
before sentence vs word	0.24 [0.02, 0.48]	1.11	0.44 [-0.56, 1.66]	0.68
before vs within word	-0.03 [-0.14, 0.09]	0.07	3.95 [3.54, 4.38]	> 100
CATO (non-dyslexic, unmasked)				
before sentence vs word	1.27 [0.98, 1.55]	> 100	-0.36 [-1.41, 0.69]	0.67
before vs within word	-0.1 [-0.38, 0.21]	0.2	4.05 [3.2, 4.91]	> 100
GE2 (unmasked)				
before sentence vs word	0.9 [0.76, 1.04]	> 100	2.15 [1.6, 2.75]	> 100
before vs within word	0.44 [0.17, 0.69]	26.78	2.76 [2.24, 3.28]	> 100
LIFT				
before sentence vs word	0.21 [-0.05, 0.48]	0.5	-0.53 [-1.04, 0.08]	1.61
before vs within word	0.17 [-0.32, 0.53]	0.41	2.48 [1.81, 3.22]	> 100
PLanTra				
before sentence vs word	0.57 [0.4, 0.74]	> 100	0.16 [-0.25, 0.57]	0.28
before vs within word	0.36 [0.16, 0.56]	55.53	2.3 [1.9, 2.7]	> 100
SPL2 (L1)				
before sentence vs word	1.17 [1.02, 1.3]	> 100	1.23 [0.59, 1.88]	> 100
before vs within word	0.48 [0.16, 0.76]	9.07	3.3 [2.56, 4.08]	> 100

Note. PI = probability intervals. BF = evidence in favour of the alternative hypothesis over the null hypothesis.

Appendix J

Simulation

A possible concern with these results – substantially better predictive performance for two-distribution mixture models – is that, in principle, as the mixture model has more parameters it might always lead to a better fit. We addressed this concern before by using cross-validation techniques for model comparison which is preventing overfitting models. To address this concern we repeated a comparison for a single distribution model and a two-distributions mixture model for two sets of simulated data that were simulated either with a single distribution or two-distributional process at heart. In other words, this allows us to test the predictive performance of our models in a context where we know the true underlying data generating process – single distribution vs two distributions – and we can test whether these models can successfully uncover the true parameter value.

In particular, the first data set was simulated using a two-distributions mixture model with two mixture components similar to the process described above (equation A4). This process and the corresponding Bayesian model is summarised in equation J1.

$$
\begin{aligned}
y \sim \ & \theta \times \log\mathcal{N}(\beta + \delta, \sigma_1^2) + \\
& (1 - \theta) \times \log\mathcal{N}(\beta, \sigma_2^2) \\
\text{constraint: } & \delta, \sigma_2^2, \sigma_1^2 > 0 \\
& \sigma_1^2 > \sigma_2^2
\end{aligned}
\tag{J1}
$$

This model is largely identical to the models before but reduced to its main parameters (but not mixed effects for participants). The model includes two log-normal distributions with a mixing proportion θ of which the distribution of shorter values has a mean of β and a standard deviation σ_2^2; the second distribution of longer values is constrained to have a mean that is larger by a factor of δ and has a larger standard deviation σ_1^2.

In R, data that follow the model in equation J1 can be simulate using a helper function called `molg` (mixture of log Gaussians).

```r
# Function for a mixture of log Gaussians
molg <- function(n, theta, mu1, mu2, sigma1, sigma2) {
  y0 <- rlnorm(n, mean = mu1, sd = sigma1)
  y1 <- rlnorm(n, mean = mu2, sd = sigma2)
  mix <- rbinom(n, size = 1, prob = theta)
  y <- y0 * (1 - mix) + y1 * mix
}


N <- 1000 # number of subjects
beta <- 5 # mean of fluent key intervals (in log)
delta <- 1 # slowdown for hesitant interkey intervals (in log)
theta <- .35 # propotion of hesitations
sigma <- c(.25, .5) # trial-by-trial error


# Generate data from a mixture of two log-Gaussians
y <- molg(n = N,
          theta = theta,
          mu1 = beta,
          mu2 = beta + delta,
          sigma1 = sigma[1],
          sigma2 = sigma[2])
```

The second data set was generated with a single distribution log-Gaussian process. The model and its corresponding Bayesian model is summarised in equation J2.

$$y \sim \log\mathcal{N}(\beta, \sigma^2)$$

$$\text{constraint: } \sigma^2 > 0 \tag{J2}$$

Data following the distirbution in equation J2 can be simulated using a few lines of R code:

```r
N <- 1000 # number of subjects
beta <- 5 # Population mean
sigma <- .25 # trial-by-trial error


# Generate data from a log normal distribution
y <- rlnorm(n = N, mean = beta, sd = sigma)
```

Again, this model is a simplified version of the single distribution models used in the main analysis. The model assumes a log-Gaussian distribution with a mean parameter β and a standard deviation σ^2.

The parameter values used for each of the two data simulations can be found in Table J1. The simulated data are visualised in Figure J1. Parameter values were chosen so that the simulated data are roughly similarly distributed to keystroke transitions.

For each of these two data sets we simulated 1,000 observations. We run 2 models – a two-distribution mixture model and a single-distribution model – each for both data sets. Models were run with 3 chains, with each 6,000 iterations of which 3,000 were warmup. Estimates with 95% probability intervals are shown in Table J1. The parameters are shown by type of data generating process along with the true parameter values. Parameter value estimates are shown by type of Bayesian model. The results show that either of the two Bayesian models succesfully uncovered the model parameters of the data with its corresponding data generating process, as shown in Table J1, but less so when the model was
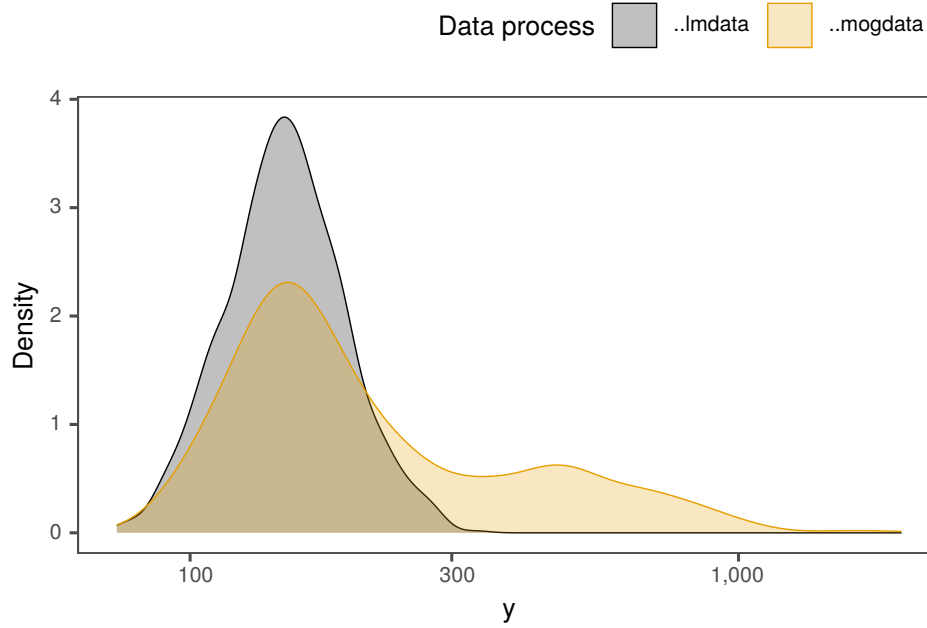
Figure J1

Data simulated with a two-distribution (grey) and a single-distribution (yellow) random data generating process. The x-axis showing the outcome y was log-scaled for visability.

applied to data generated with the incorrect underlying process. Particularly the mixing proportion θ and the slowdown parameter δ were not uncovered at all by they single-distribution model.

We used LOO-CV to compare the predictive performance of the two models for each data generating process. The model comparisons can be found for each data generating process in Table J2. The results rule out the possibility that the mixture model does always lead to higher predictive performance. Indeed, the mixture model showed a slightly lower predictive performance for the data that were generated with a single-distribution process. However, for the data generated with a two-distribution mixture process, the mixture model shows a substantially higher predictive performance. In fact, the mixture model's predictive performance is 11.6 standard errors higher compared to the single-distribution model. In comparison, for the single-distribution data, the two-distributions mixture model was negligibly different from the single-distribution model with a difference of 0.77 standard

Table J1

Uncovered parameter estimates with 95% probability interval (PI) and true parameter values for each simulated data set and by model and their respective parameters.

Parameter with true value	Estimate with 95% PI	
	Two-distributions model	Single-distributions model
Two-distributions data		
$\beta = 5$	5.02 [4.99, 5.04]	4.93 [4.76, 5.01]
$\delta = 1$	1.04 [0.92, 1.14]	0.13 [0.01, 0.3]
$\theta = .35$	.33 [.28, .39]	.54 [.11, .92]
$\sigma_1^2 = 0.25$	0.25 [0.23, 0.27]	0.22 [0.16, 0.25]
$\sigma_2^2 = 0.5$	0.49 [0.42, 0.57]	0.25 [0.22, 0.3]
Single-distribution data		
$\beta = 5$	5.35 [5.32, 5.39]	5 [4.99, 5.02]
$\sigma = 0.25$	0.6 [0.57, 0.63]	0.25 [0.24, 0.26]

errors. Thus, the single distribution is more parsimonious.

Table J2

Model comparisons by data set. The top row shows the models with the highest predictive performance for each data generating process. Standard error is shown in parentheses.

Model	$\Delta\widehat{elpd}$	$\widehat{elpd}$
Data: Two-distribution mixture process		
Two-distribution mixture model	–	-6,068 (41)
Single-distribution model	-191.3 (16.5)	-6,259 (38)
Data: Single-distribution process		
Single-distribution model	–	-5,030 (24)
Two-distribution mixture model	-0.5 (0.7)	-5,030 (24)

Note. $\widehat{elpd}$ = predictive performance indicated as expected log pointwise predictive density; $\Delta\widehat{elpd}$ = difference in predictive performance relative to the model with the highest predictive performance in the top row.