Morphemes as letter chunks:

Discovering affixes through visual regularities

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Abstract

During visual word processing readers identify chunks of co-occurring letters and code for their typical position within words. Using an artificial script, we examined whether these phenomena can be explained by the ability to extract visual regularities from the environment. Participants were first familiarized with a lexicon of pseudoletter strings, each comprising an affix-like chunk that either followed (Experiment 1) or preceded (Experiment 2) a random character sequence. In the absence of any linguistic information, chunks could be defined only by their statistical properties - similarly to affixes in the real language, chunks occurred frequently and assumed a specific position within strings. In a later testing phase, we found that participants were more likely to attribute a previously unseen string to the familiarization lexicon if it contained an affix, and if the affix appeared in its typical position. Importantly, these findings suggest that readers may chunk words using a general, language-agnostic cognitive mechanism that captures statistical regularities in the learning materials.

Keywords: visual word identification, morphology, artificial script, chunking, statistical learning

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The cognitive system is tuned to detect the probabilistic patterns present in the environment. During even a brief exposure, people learn about the various statistical properties of perceptual events, including distributional variability, frequency, and probability with which events co-occur. Importantly, such learning has been demonstrated for different types of materials, contexts, and cognitive domains (for reviews, see Armstrong, Frost, & Christiansen, 2017; Aslin, 2017; Aslin & Newport, 2012; Christiansen, 2019; Frost, Armstrong, & Christiansen, 2020; Newport, 2016; Saffran & Kirkham, 2018; Thiessen, Kronstein, & Hufnagle, 2013).

One domain for which the ability to extract statistical information has been particularly well evidenced is visual processing. Specifically, observers are known to compute co-occurrence probabilities for visual objects, both when these objects are presented sequentially or embedded within complex scenes. In a seminal study by Fiser and Aslin (2001), participants passively viewed scenes composed of multiple abstract shapes that were arranged in a seemingly coincidental manner. Unbeknownst to the participants, shapes were organized into base pairs (i.e., pairs consisting of shapes that were always presented together). After being familiarized with the scenes, participants were asked to choose between base pairs and foil pairs (i.e., pairs that shared the properties of base pairs, but consisted of shapes that were never presented together during familiarization). The results revealed that participants were able to distinguish base pairs from foils with above-chance accuracy, suggesting that they must have extracted shape co-occurrence probabilities (for similar results, see Bulf, Johnson, & Valenza, 2011; Chun & Jiang, 1999; Fiser & Aslin, 2002; Turk-Browne, Jungé, & Scholl, 2005).

Further studies suggested that the extraction of statistical information may contribute to the formation of complex visual representations. In Fiser and Aslin (2005; Experiment 4), participants were familiarized with scenes built of shape pairs and quadruples, and then asked to distinguish between foil and base pairs, foil and base quadruples, and between foil and embedded pairs (i.e., pairs of co-occurring shapes that during familiarization always appeared embedded in a quadruple). The study found that, whereas participants were able to successfully tell apart foil and base pairs/quadruples, they failed to distinguish between foil and embedded pairs, implying that the co-occurrence probabilities computed for individual shapes were not retained after participants constructed the representations for pairs and quadruples.

In sum, studies have shown that observers learn probabilistic information while processing visual stimuli, and that such information may subserve the construction of higher-order visual representations (see also Frank, Goldwater, Griffiths, & Tenenbaum, 2010; Orbán, Fiser, Aslin, & Lengyel, 2008; Thiessen et al., 2013).

Curiously, it remains unclear whether the ability to extract regularities contributes to the processing of written language. On one hand, the link between the two faculties is plausible—at the orthographic level[1], written language can be conceptualized as an instance of visual stimuli, and parallels can be drawn between reading and generic visual processing (e.g., Dehaene, Cohen, Sigman, & Vinckier, 2005; Grainger, Dufau, & Ziegler, 2016). Further, visual word processing appears to be guided by the probabilistic structure of language. Beyond the well-established word frequency effect (e.g., Forster & Chambers, 1973; Monsell, 1991), readers appear to extract different kinds of regularities from printed words. For one, readers are sensitive to the consistency between the written form and other linguistic levels such as phonology and meaning. Specifically, word naming is facilitated by high orthography-to-phonology consistency, that is, words containing letter patterns that are always pronounced the same (e.g., *-ike* in *like* and *hike*) are named faster than

[1] In keeping with most of the psycholinguistic literature on orthography and morphology, we intend the term “orthographic” in its wide sense, as referring to any kind of representation or level of linguistic analysis that deals with orthographic information, no matter whether lexical (words) or sub–lexical (morphemes and letter clusters).

words containing patterns that take different pronunciations in different words (e.g., *-ave* in *have* and *gave*; e.g., Jared, 2002; Jared, McRae, & Seidenberg, 1990; Perry, Ziegler, & Zorzi, 2007). Similarly, words whose spelling provides a consistent cue to a certain meaning (e.g., *widow* in *widower*, *widowed*, *widowhood*) are processed faster compared to words with low orthography-to-semantics consistency (e.g., *whisk* in *whisker*, *whisky*, *whiskered*; Marelli, Amenta, & Crepaldi, 2015). Furthermore, readers seem to have knowledge of the spelling-to-meaning regularities typical for their native language (Ulicheva, Harvey, Aronoff, & Rastle, 2020).

However, the role of orthographic regularities becomes less clear when considering the visual aspect of word processing. Indeed, regularities are also present at a purely orthographic level where they can be derived from the distribution of letters and letter clusters in words. But while there is a general consensus that readers extract information about the patterns with which letters co-occur in words, the current empirical data provide a mixture of results as to the influence of this information on visual word processing (for a review, see Chetail, 2015). A good example of such contradictory results relates to the effect of bigram frequency. One of the earliest studies investigating this effect, rather counter-intuitively, demonstrated that words made up of bigrams with low frequency (e.g., *vodka*) were perceived faster than words with high frequency bigrams (e.g., *latin*; Owsowitz, 1963). This finding, however, received little support from subsequent studies (e.g., Chetail, Balota, Treiman, & Content, 2014), which yielded a combination of facilitatory (Biederman, 1966; Massaro, Jastrzembski, & Lucas, 1981) and null effects (Andrews, 1992; Gernsbacher, 1984; Johnston, 1978; Keuleers, Lacey, Rastle, & Brysbaert, 2012; Manelis, 1974; McClelland & Johnston, 1977) of bigram frequency on letter string processing. Finally, the same pattern of mixed findings was corroborated in a recent study by Schmalz and Mulatti (2017), who asked if bigram frequency statistics impact visual lexical decision. They analysed the data from the British Lexicon Project (Keuleers et al., 2012) and the English Lexicon Project (Balota et al., 2007), and found no evidence for bigram frequency effects in the former, and a weak inhibitory effect in the latter case (i.e., words with highly frequent bigrams were processed more slowly).

A similarly complicated picture emerges from research that tested the link between visual word processing and the ability to learn regularities. Chetail (2017) ran a study in which participants observed a flow of strings composed of unfamiliar fonts, with several bigrams occurring very frequently. Following this exposure, participants demonstrated considerable sensitivity to these high–frequency bigrams; when they appeared in previously unseen strings, these latter were judged as more similar to the familiarization strings. Moreover, participants more easily detected unfamiliar fonts that were involved in such bigrams. This demonstrates that when readers are exposed to visual materials similar to written words, they code for the frequency of orthographic units (e.g., bigrams). Although Chetail's (2017) experiment involved pseudo–linguistic materials, these data are suggestive of the possibility that readers might deploy similar learning mechanisms also when processing real letters and words.

Yet, other studies have failed to find conclusive evidence for this prediction. Schmalz, Altoè and Mulatti (2017) noted that if regularity learning is in fact implicated in reading, individuals with low reading skills should also exhibit poor statistical learning abilities. Thus, they performed a meta-analysis on studies contrasting regularity learning between dyslexic readers and controls. Although the analysis did reveal that dyslexia appears to be associated with poorer regularity learning, the main conclusion offered by Schmalz et al. (2017) is that current evidence is limited by several methodological shortcomings and, overall, insufficient.

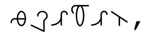
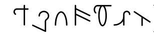
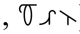
We propose that morphology offers a promising new venue for investigating the role of regularity learning in visual word processing. After all, morphemes can be seen as chunks of letters that frequently occur together (by virtue of their association with a piece of meaning); from this point of view, there is a considerable similarity between written (morphologically-complex) words and the visual stimuli used in statistical learning studies (e.g., Fiser & Aslin, 2005).

Importantly, the idea that morphology may be rooted into the statistics of language is deeply embedded into the connectionist approach to morphology (e.g., Plaut & Gonnerman, 2000) and other recent theories of visual word identification (e.g., Baayen, Milin, Durdevic, Hendrix, & Marelli, 2011). The core idea is that the visual word identification system does not need to have explicit morphological representations in order to produce morphological effects. Neural networks that learn to map form onto meaning (and/or orthography to phonology) may display what can be interpreted as sensitivity to morphemes based on statistical regularities in this mapping. Moreover, a possible link between language statistics and morphological processing has recently been considered also in some localist accounts of morphology. For example, the dual-route model of Grainger and Ziegler (2011) proposed that the fine-grained route of orthographic processing is sensitive to letter co–occurrence statistics. When processing along this route, readers identify frequently co–occurring letters and chunk them into higher–level orthographic representations (which include morphemes in this model). Although this account does not specify what process is responsible for the formation of chunks, it does imply that chunking relies on statistical information about the recurrence of orthographic forms.

Interestingly, the possible link between statistical learning and visual word processing is corroborated by several phenomena reported in the morphological processing literature. First, numerous studies showed that readers see morphological structure also in words that only have the orthographic appearance of being complex (e.g., *iron-y* or *corn-er*), but whose meaning has nothing to do with the meaning of their pseudo-stems (e.g., *irony* is not an object that looks to be made of iron and *corner* is not someone who corns; Amenta, Marelli, & Crepaldi, 2015; Longtin, Segui, & Hallé, 2003; Rastle, Davis, & New, 2004; for a review, see Amenta & Crepaldi, 2012). These findings suggest that visual word processing may partly rely on orthographic representations for commonly encountered letter clusters (e.g., readers may have a representation for *er* because it frequently occurs in the lexicon; Rastle & Davis, 2008).

Another phenomenon that appears to be closely related to the extraction of statistical information is the position-specificity effect. Many morphemes, like derivational affixes, have a fixed position within complex words (e.g., prefixes such as *pre, re, mis* typically occur at the beginning, while suffixes such as *er, ful, ness* appear at the end of words), whereas others, like stems, can distribute freely (e.g., the stem *view* can appear in the initial position as in *viewer*, in the final position as in *review*, or even in the middle word position as in *reviewer*). Importantly, there is evidence that readers are sensitive to this information. In a visual lexical decision paradigm, Crepaldi, Rastle, and Davis (2010) demonstrated that nonwords that had no morphological structure (e.g., *gasfil*) were easier to reject than nonwords composed of a real stem and a real affix (e.g., *gasful*), but only if the affix appeared in its typical position (e.g., *filgas* and *fulgas* were equally easy to reject). Further, Crepaldi, Rastle, Davis and Lupker (2013) found that manipulating the within-word position did not have a similar effect on the identification of stems. Thus, affixes, but not stems, appear to be processed in a position-specific manner, consistently with the possibility that readers might represent the probability of morphemes appearing in a given position within words.

In sum, there is theoretical and empirical precedence for investigating whether regularity learning impacts the morphological processing of written words. However, we are aware of no experimental demonstration of this hypothesis. In the morpho–orthography literature and in the work on morpheme position specificity, the link between morphological processing and the ability to extract statistics can only be inferred post–hoc, as none of the relevant studies directly manipulated the statistical properties of the stimuli. Moreover, it remains unclear whether morphemes can be identified based on visual-orthographic information alone, since previous studies investigating this issue used real linguistic materials, which makes it impossible to rule out the involvement of semantics or phonology.

To address these shortcomings, we developed a hybrid paradigm drawing on statistical learning and psycholinguistic research. In two experiments, readers were familiarized with pseudoletter strings (e.g., , ), and we tested whether they formed representations for affix-like chunks embedded within those strings (henceforth, *affixes*; e.g., ). In the absence of any linguistic content, affix representations could be constructed only using the statistical information extracted from the familiarization lexicon - much like affixes in the real language, affixes in our study were clusters of frequently co-occurring characters, and appeared in a fixed position within the familiarization strings. Thus, evidence for position-specific affix representation would corroborate the hypothesis that visual processing of real words is supported by the language-agnostic ability to extract regularities from visual materials.

Experiment 1

In Experiment 1, participants first completed a familiarization phase where they observed a large number of pseudoletter strings. Unbeknownst to participants, strings were composed of a random pseudoletter sequence followed by an affix, that is, a cluster of frequently co-occurring pseudoletters. Next, in a testing phase, participants saw further, previously unseen strings, and were asked to judge whether or not these strings belonged to the familiarization lexicon. Critically, we manipulated the presence and position of the affixes within the testing strings: Participants saw (a) affix-present strings where affix position was the same as in the familiarization strings, (b) affix-present strings where affix position was different than in familiarization, and (c) affix-absent strings (henceforth, *position-congruent*, *position-incongruent*, and *affix-absent* strings, respectively). We hypothesized that, if readers use statistical information to identify affixes within strings, they should more often produce a “yes” response (i.e., ascribe a string to the familiarization lexicon) for affix-present strings, as compared to affix-absent strings; and if such affix identification is position-specific, we should observe more “yes” responses for position-congruent than for position-incongruent strings.

In addition to our main investigation, we considered the possibility that some cognitive or perceptual process could interfere with the participants’ ability to discover the affixes. For example, there is evidence for a preferential deployment of attention to materials located in the beginning of strings (Aschenbrenner, Balota, Weigand, Scaltritti, & Besner, 2017), a tendency which could potentially limit the learning of string-final affixes. Alternatively, learning could benefit from the fact that Italian, the native language of our participants, is suffix-dominant (e.g., Dryer, 2013), which could encourage the processing of materials located at the end of strings. To determine whether our participants demonstrated a preference for either position, we carried out an additional affix detection task where we tested if participants' ability to detect the affixes from the familiarization phase varied depending on affix position (i.e., string-initial vs. string-final).

Methods

Raw data, analysis scripts, experiment scripts, stimuli, and additional details about the project are available at the study's page at Open Science Framework: https://osf.io/y52q7/

Participants. We recruited 70 Italian native speakers, who did not use any other languages on a daily basis, had normal or corrected-to-normal vision, no learning disorders, and were 18-35 years old. All participants gave informed consent prior to the experiment and received 5€. All experimental procedures were approved by the Ethics Committee at Scuola Internazionale di Studi Superiori Avanzati (International School for Advanced Studies), where participants were tested.

Apparatus. Participants sat in front of a 27'' BenQ XL2720 monitor and responded using keys J and F on an English QWERTY keyboard. Stimuli were displayed in black, against a light gray background (#f0f0f0). The experiment was programmed in OpenSesame (v. 3.1.9; Mathôt, Schreij, & Theeuwes, 2012). Participants carried out the experiment individually in a sound-proof booth.

Stimuli and procedure. Participants completed a main task, consisting of a familiarization and a testing phase, followed by an additional affix detection task. The testing took place in one session, which lasted about 30 minutes.

Familiarization phase. First, participants were explained they would see words written in alien letters and only asked to attentively observe them. At this stage, they were given no further information. They then saw the familiarization strings appearing one by one in the center of the screen (800ms ON, 200ms OFF).

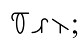
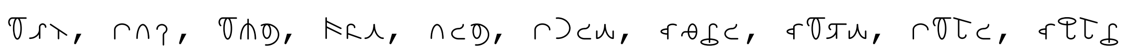
In the familiarization phase, we exposed participants to 200 strings built of pseudoletters (BACS-2, sans-serif; Vidal, Content, & Chetail, 2017). Strings were six to eight characters long, and were composed of a random sequence of pseudoletters followed by an affix (i.e., a cluster of frequently co-occurring pseudoletters). We used 10 unique affixes, half of which were three letters, and half four letters long (e.g., ; Table 1). Each affix was attached to twenty different random sequences (e.g., ).[2] We ensured that affixes did not share more than two adjacent characters with any other affix or sequence used in the experiment.

Table 1. *Experiments 1-2: A Complete List of the Affixes Used in Our Experiments.*

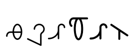
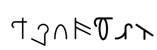
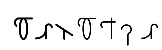
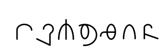


Testing phase. In the testing phase, participants saw further, previously unseen strings, and were asked to categorize them as either words from the alien language seen in familiarization or character combinations that did not belong to the familiarization language. Participants were not informed what would be the proportion of words or how many items in total they would see. Each trial started with a central fixation cross (500ms), followed by the presentation of a string. After participants had responded (or after a 2000 ms time-out), the string was removed from the screen and the next trial started.

[2]Affix statistics in real languages are obviously not so clear–cut, but rather vary across and within languages (e.g., some affixes are more productive than others). However, given the small number of affixes used in this study and in the interest of experimental control, we opted for a simplified distribution.

Participants saw 300 testing strings whose structure differed depending on the condition, specifically: (a) 100 position-congruent strings composed of a random pseudoletter sequence and an affix appearing in the final position, (b) 100 position-incongruent strings composed of a random sequence and an affix in the initial position, and (c) 100 affix-absent strings composed of two random sequences (examples in Table 2). The strings were presented intermixed and the order of presentation was randomized for each participant. Testing strings were created by concatenating new random sequences with the affixes used in familiarization. Each affix appeared attached to ten different random sequences in condition (a) and (b), respectively. To accommodate for the unlikely possibility that our position manipulation was confounded by systematic differences in the sequences used in position-congruent vs. position-incongruent strings, we created two lists of 100 random sequences whose use across position-congruent and position-incongruent strings was counterbalanced between participants (control analyses found no effects related to sequence lists; see Supplementary Materials).

Table 2. *Experiment 1: Examples of Stimuli Used in the Familiarization (leftmost column) and Testing (the three remaining columns) Phase of the Experiment. For Illustration Purposes, Affixes are Marked in Bold.*

familiarization	position-congruent	position-incongruent	affix-absent
			

Affix detection task. Finally, in the affix detection task, participants were shown a screen containing the familiarization affixes and asked to spend 3 minutes memorizing them. Next, they saw further strings, presented as in the testing phase, and pressed a button to determine whether or not a string contained one of the affixes (participants were told that an affix might appear in any part of the string). Participants saw 120 strings: (a) 40 strings composed of a random sequence and an affix in the string-final position, (b) 40 strings composed of a random sequence and an affix in the string-initial position, and (c) 40 strings composed of two random sequences.

Statistical analysis. Data from the testing phase were modeled using a Generalized Linear Mixed Model (GLMM) involving a fixed effect for String Type (affix-absent vs. position-congruent vs. position-incongruent), by-participant random intercepts and slopes, and by-item random intercepts. Given the binary nature of the dependent variable, the model was a logistic regression (see Supplement for model syntax). The reference level for String Type was initially set to affix-absent, so as to examine the comparison between affix-absent and position-congruent strings, and between affix-absent and position-incongruent strings. This allowed us to investigate the effect of the mere presence of an affix. Next, the reference level for String Type was changed to position-congruent, so as to assess the comparison between position-congruent and position-incongruent strings and thus to investigate the effect of affix position. We applied effect-coded contrasts in all GLMMs reported in this paper. Models were computed in R (version 3.4.2; R Core Team, 2017), using the *lme4* package (version 1.1-14; Bates, Maechler, Bolker, & Walker, 2019). See Supplement for further models confirming the solidity of our effects.

Data from the affix detection task were analysed using d-prime, which was computed with the standard formula d' = z(H) - z(FA) where H is the hit rate (i.e., the number of correct affix detections divided by the number of trials where an affix was present), and FA is the false alarm rate (i.e., the number of incorrect affix detections divided by the number of trials where an affix was *not* present). We calculated d-prime separately for each participant in each condition (string-initial vs. string-final), thus assessing the rate of successful affix detection as depending on within-word position. This approach left us with two paired data points per participant, making it unnecessary to use sophisticated mixed-effect modelling; d-primes for string-initial and string-final position were thus compared with a paired-sample t-test.

Results

Prior to data analysis, we excluded 1 participant who judged 99% of the testing strings as belonging to the familiarization lexicon (leaving $n = 69$; the histograms used to identify outliers can be found in Figure S1 in the Supplement).

Data from the testing phase are illustrated in Figure 1 (means in Table S1). The analysis revealed that both types of affix-present strings were associated with greater odds of making a "yes" response, as compared to affix-absent strings (position-congruent strings: $\hat{\beta} = .274$, $z = 4.47$, $p < .001$; position-incongruent strings: $\hat{\beta} = .176$, $z = 2.86$, $p = .004$; the overall effect of String Type was also significant: χ^2 (2) = 20.02, $p < .001$). Thus, participants were more prone to ascribe a string to the familiarization lexicon if it contained an affix. However, the comparison of position-congruent and position-incongruent strings was only marginally significant ($\hat{\beta} = -.097$, $z = -1.90$, $p = .057$). Model estimates for the proportion of "yes" responses were as follows: .51 (95% CI: .48 to .55) for affix-absent strings, .58 (95% CI: .55 to .61) for position-congruent strings, and .56 (95% CI: .53 to .59) for position-incongruent strings.

Additionally, the analysis of the affix detection task showed a clear advantage for the string-initial position—participants' ability to detect affixes was higher when they appeared at the beginning of a string, rather than at the end ($t(62) = 3.07$, $p = .003$, Cohen's $d = 0.39$; means in Table 3; prior to this analysis, we excluded further 5 participants who produced less than 33% responses in any design cell, and 1 participant who had an outlier d-prime value -0.75, thus leaving 63 participants).

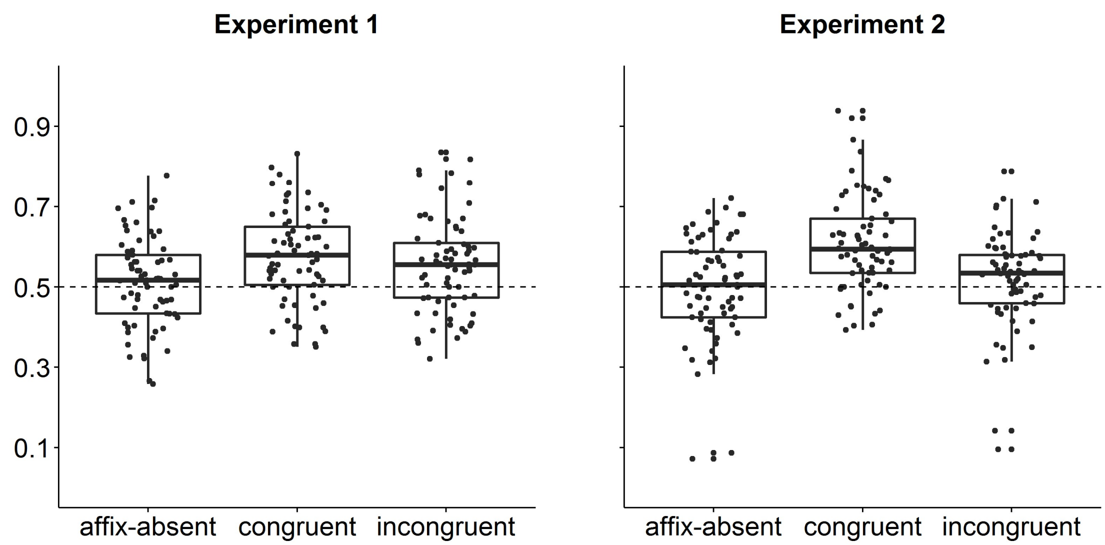


Figure 1. Experiments 1-2: Boxplots presenting the proportion of strings judged as belonging to the familiarization lexicon, by affix-absent, position-congruent, and position-incongruent testing strings.

Table 3. *Experiments 1-2: Mean Affix Detection (d-prime), by String-Initial and String-Final Affix Position. Means Reported with 95% Confidence Intervals.*

	string-initial	string-final
Experiment 1	1.01 [±.12]	0.88 [±.13]
Experiment 2	1.05 [±.12]	0.80 [±.15]

Discussion

Experiment 1 suggested that readers may identify morphemes based solely on probabilistic information: After being familiarized with strings containing recurring affixes, participants became sensitive to the presence of these affixes in previously unseen strings (i.e., they more often judged such strings as belonging to the familiarization lexicon if they contained an affix). Importantly, despite being in other ways similar to real words, our stimuli were built of pseudoletters, and so were devoid of any semantic, syntactic or phonological content. Thus, participants must have learnt to distinguish the affixes based on the statistical properties of their constituent characters (see Rastle & Davis, 2008).

We also found some evidence that such probability-based identification of morphemes is sensitive to the position of morphemes within strings: Position-congruent strings, which comprised an affix appearing in the same position as during familiarization, were ascribed to the familiarization lexicon slightly more often than position-incongruent strings. However, the associated statistical effect was small and only marginally significant, raising the possibility that this finding may constitute a null effect. Alternatively, an external cognitive or perceptual process could have interfered with the ability to encode the information related to affix position, thus resulting in a diminished statistical effect.

Interestingly, data from the affix detection task supported this latter interpretation: We observed that participants were better able to detect the affixes when they appeared in string-initial vs. string-final position, suggesting a processing advantage for string-initial affixes. Thus, our results speak to the possibility that participants might indeed learn about both presence and position of affixes, but a preference for string-initial materials can at times (e.g., when affixes are located at the end of strings) interfere with coding for affix position.[3] To validate this interpretation, and to assess the robustness of our overall findings, we conducted Experiment 2.

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[3]Another possibility was that the string-initial bias affected how participants processed the testing strings - string-initial affixes might have been more visible within those strings. However, it is unlikely that such bias could influence responses in the testing phase given the long response window (2000ms). In any case, this account would preserve the idea that participants identified the affixes in a position-specific manner; the effect would just emerge less strongly in the data because of a concomitant bias that acted in the opposite direction with respect to our experimental manipulation.

Experiment 2

Experiment 2 was a replication of Experiment 1, except that now affixes appeared in the beginning (rather than at the end) of the familiarization strings. Once again, we investigated whether participants would become sensitive to the presence and position of affixes following familiarization. We expected to replicate the effect of affix presence. But importantly, if we correctly reasoned that a preference for string-initial materials limited participants' ability to code for positional information in Experiment 1, in Experiment 2 we should observe a statistically significant effect of affix position, since a string-initial bias would no longer interfere with affix learning during familiarization.

Methods

Raw data, analysis scripts, experimental scripts and stimuli are available at Open Science Framework: https://osf.io/y52q7/

Participants. We recruited further 71 participants from the same population as in Experiment 1. Monetary compensation, informed consent, and ethical approval were arranged as per Experiment 1.

Stimuli, procedure and statistical analysis. The stimuli were identical as in Experiment 1, with the exception that affixes were now positioned at the beginning of the familiarization strings (i.e., we transformed the affix-present strings used in Experiment 1 by moving the affixes to the front of the strings; affix-absent strings remained the same); all other features of the stimuli remained unchanged. We used the same apparatus and replicated the procedure of Experiment 1. The data were also modeled exactly as in Experiment 1.

Results

Before analyzing the data, we excluded 2 participants who judged the majority of the testing strings (86% and 98%) as belonging to the familiarization lexicon (leaving n = 69; see Figure S1 for a histogram used to identify outliers).

The analysis of the testing phase revealed a very similar pattern of results relative to Experiment 1 (see Figure 1; Table S1). Just as in Experiment 1, the overall effect of String Type was statistically significant (χ^2 (2) = 18.99, p < .001), and the odds of making a “yes” response were greater for position-congruent than for affix-absent strings ($\hat{\beta}$ = .516, z = 4.31, p < .001). However, the difference between position-incongruent and affix-absent strings did not reach the conventional significance threshold ($\hat{\beta}$ = .101, z = 1.42, p = .155). Participants were therefore prone to make a “yes” response when an affix was present, but this time only if the affix was located in the same position as in the familiarization phase. This finding was further confirmed by the comparison between position-congruent and position-incongruent strings, which was now statistically significant ($\hat{\beta}$ = -.415, z = -3.87, p < .001), as predicted. Model estimates for the proportion of “yes” responses were as follows: .50 (95% CI: .45 to .54) for affix-absent strings, .62 (95% CI: .59 to .66) for position-congruent strings, and .52 (95% CI: .49 to .55) for position-incongruent strings; additional analyses showed that these results remain stable under different outlier exclusion criteria (see Supplement).

We also assessed the robustness of our finding that affixes are more easily detected if they appear in the string-initial position. This test was important because a pattern of results consistent with Experiment 1 would suggest that such string-initial bias is most likely due to some process external to our task (rather than being a product of the exposure to the familiarization lexicon, for example). Indeed, we once again found that affix detectability was higher for affixes in the string-initial rather than string-final position (t(67) = 3.94, p < .001, Cohen’s d = 0.48; means in Table S3; prior to this analysis, we excluded 1 further participant who had an outlier d-prime value 2.66, leaving 68 participants).

Discussion

Experiment 2 confirmed the core finding of Experiment 1: Following familiarization, participants were sensitive to the presence of affixes within strings. However, this was only true for position-congruent strings in this experiment. Affix-present, but position-incongruent strings were ascribed to the familiarization lexicon similarly often as affix-absent strings, and significantly less often than position-congruent strings. Thus, unlike in Experiment 1, participants in Experiment 2 were clearly sensitive to whether affixes appeared in the same position as in familiarization (additional analyses confirmed that the effect of affix position was indeed greater in Experiment 2; see Supplement).

The difference between the results of Experiment 1 and Experiment 2 with respect to the position coding effect is naturally explained by the bias uncovered in the affix detection task: Participants appeared to process affixes more easily when they appeared string-initial. The fact that affixes were located at the end of the familiarization strings in Experiment 1 might have interfered with participants' ability to process the affixes, thus constraining learning. But because in Experiment 2 familiarization affixes were presented string-initial, the encoding of the positional information was not disturbed, allowing participants to later use this information in the testing phase. Also note that the results that emerged in the detection task across experiments imply that the string-initial bias is not a product of the exposure to the statistical properties of the familiarization lexicon, but likely comes from perceptual or cognitive mechanisms independent of the task. Overall, these data point to an important role for position in affix coding, similarly to what Crepaldi et al. (2010) found for real affixes.

General Discussion

Evidence in the visual word identification literature suggests that the ability to extract statistical regularities in letter co-occurrence may play an important role in the learning and processing of morphemes (e.g., Kazanina, 2011; Marelli, Amenta, Morone, & Crepaldi, 2013; Rastle & Davis, 2003; Rastle et al., 2004). We tested this hypothesis by investigating if readers use statistical information to discover affix-like chunks embedded in pseudoletter strings. Critically, since they were devoid of any phonemic or semantic information, our chunks resembled real morphemes only in the sense that they were clusters of characters occurring together across multiple different strings. We demonstrated that a brief familiarization with strings containing these chunks was sufficient for participants to: (i) develop sensitivity to affix-like chunks; and (ii) code for their position within strings.

These results mirror two important phenomena observed in the processing of real linguistic materials. First, similarly to how our participants were sensitive to chunks within pseudoletter strings, readers are known to be sensitive to the presence of morphemes and morpheme-like clusters in strings of familiar letters. For example, readers reject nonwords more slowly when they contain morphemes (e.g., *applement*; Crepaldi, et al., 2010; Caramazza, Laudanna, & Romani, 1988; Taft & Forster, 1975; see also Amenta & Crepaldi, 2012; Feldman, Kostić, Gvozdenović, O'Connor, & del Prado Martín, 2012; Hasenäcker, Solaja, & Crepaldi, 2020; Rastle & Davis, 2008). Although particular interpretations of this phenomenon may vary, overall studies have demonstrated that morphologically-structured nonwords appear more word–like to the readers. Similarly, in our study, strings comprising an affix-like chunk were more likely judged as part of the familiarization lexicon.

Second, we saw that the processing of chunks varied depending on whether they appeared in their typical position, a finding that closely resembles the position-specificity effect observed in the identification of real affixes within nonwords. Crepaldi et al. (2010) found that nonwords comprising a real suffix (e.g., *gasful*) were rejected in lexical decision more slowly than non–suffixed controls (e.g., *gasfil*), but only when the suffix was in its typical position (*fulgas* was as easy to reject as *filgas*). Similarly, our participants tended to consider novel strings as belonging to the familiarization lexicon particularly when the affix–like chunks appeared in their typical position.

Hence, our study suggests that some of the mechanisms involved in morphological processing can operate based only on visual-orthographic information, in isolation from other linguistic levels (e.g., semantics or phonology). By constructing the stimuli of unfamiliar pseudoletters, we ensured that semantics, phonology and syntax were not available, and so the cognitive processes that allowed readers to become sensitive to the presence and position of the affix-like chunks must have been based exclusively on visual information.

This resonates with the morpho-orthographic accounts of visual word processing (e.g., Crepaldi, Rastle, Coltheart & Nickels, 2010; Rastle & Davis, 2008). In this view, at the early stages of processing, readers perform a rapid analysis of the orthographic structure of words, which leads them to discover genuine morphemes in the case of morphologically complex words (i.e., the stem *deal* and the affix *er* in the word *dealer*); but also pseudo-morphemes in the case of simple words with the mere appearance of morphological complexity (i.e., the pseudo-stem *corn* and the pseudo-affix *er* in the word *corner*). The morpho-orthographic account emphasizes the nature of morphemes as clusters of letters that co-occur frequently; for instance, it highlights that semantics is not indispensable for the identification of potential morphemes. However, it does not consider morphemes as entirely equivalent to letter clusters, of course. For instance, it does not preclude that semantic information also plays a role in written word processing (e.g., Amenta et al., 2015; Feldman et al., 2012; Marelli et al., 2015).

More generally, morphemes are certainly important in language because they connect to meaning. Frequent clusters of letters may also be psychologically relevant because they represent phonemes, syllables, or other linguistically relevant information. This network of connections with the linguistic system was entirely absent in the experiments presented here. It is important to stress that this does not imply that we deny the importance of this network. Of course, morphemes in the real language are more than mere letter chunks, and surely there are several aspects in their processing that depend crucially on their connections with meaning or phonology. Thus, our study should be taken as an important early step showing that, despite some aspects of morphological processing surely depend on the widespread connections present throughout the language processing system, some other morphological phenomena may be described as primarily orthographic, to the point that they emerge even in artificial systems where semantics, phonology and syntax are not implemented.

Beyond highlighting the importance of orthographic information, our data suggest that morphological processing is affected by the statistical regularities that characterize the reading materials. This is consistent with much previous work. The idea that morphological processing is statistical in nature can be traced back to Seidenberg (1987) who suggested that morphological units, or sub–lexical units more generally, emerge based on orthographic regularities. Although this early account did not specify what type of regularities may be taken up by the system (e.g., occurrence frequency, transitional probability), it stressed that sub–lexical units are based on the distribution of letter patterns in the lexicon (see also Seidenberg & McClelland, 1989).

A similar approach has been taken by numerous other scholars. Rueckl et al. (1997) constructed a connectionist network which involved orthographic and semantic nodes (reflecting the connections between orthography and semantics in the real language), but which was devoid of any explicit representations for morphological units or ties. The model was successfully able to recreate the morphological priming effect (e.g., Stanners, Neiser, Hernon, & Hall, 1979), suggesting that this effect must therefore be captured by the statistical associations between orthography and semantics (see also Plaut & Gonnerman, 2000).

Baayen et al. (2011) proposed a model including a layer of form representations (i.e., letters and bigrams) and a layer of semantic representations (i.e., meanings). The model associates form and semantic representations through discriminative learning (e.g., Wagner & Rescorla, 1972): When letters and bigrams co–occur with a given meaning (e.g., *h* and *ha* with the meaning HAND), their association is strengthened, proportionally to how many other letters and bigrams are also present in the input. Conversely, letter-to-meaning associations are weakened when letters and bigrams are present, but a piece of meaning is not (e.g., *h* and *ha* appearing in the word *hat*, which has nothing to do with the meaning HAND). Importantly, and just as in Rueckl et al.'s (1997) network, no representations for morphemes or morphological ties were built into this model, and yet it was able to account for several morphological effects (e.g., family size effect; Schreuder & Baayen, 1997). This again suggests that the processing of written words makes use of the regularities in how different levels of linguistic information map onto one another.

The learning of these mappings has also been addressed experimentally in several studies using artificial stimuli, either novel words made up of existing letters attached to meaning (e.g., Merkx, Rastle, & Davis, 2011; Rueckl & Olds, 1993; Tamminen, Davis, & Rastle, 2015) or strings of pseudofonts attached to phonology (e.g., Taylor, Davis, & Rastle, 2017; Taylor, Rastle, & Davis, 2019). These experiments exploited the statistical regularity in the stimuli (e.g., consistency in the link between morphemes and meaning); in this sense, we walk on a pathway they set, and build on the same approach of using artificial, pseudo–linguistic materials to offer suggestions about the processing of the real language.

The findings from the present study are convergent with these accounts, insofar that they suggest that morphological processing is, at least in part, guided by the rich statistical information encoded in language. But our study presents an important element of novelty that we would like to emphasise. Previous research focused primarily on the regularity in the mapping between different linguistic levels of representation - for example, orthography to phonology, or orthography and phonology to semantics. In the present study, however, there is no other linguistic information to map orthography to; the focus is all on the visual input, whose statistical regularity is taken up even in the absence of any phonology or semantics to associate this visual input with. From this perspective, it is all the more impressive that in our experiments “letters” were in fact unknown, non–linguistic symbols, and “words” and “affixes” were nothing more than sequences of these symbols. This shows the power of statistical regularities - they might affect word processing even when the usual connections between different levels of linguistic information are ruled out.

Where does the sensitivity to regularities in character distribution come from? The results described here suggest that linguistic, and specifically orthographic regularities may be acquired through a statistical learning mechanism. Readers in our study passively observed a stream of familiarization strings and learnt which characters may be clustered into affix-like chunks. Because stimuli were constructed of unfamiliar pseudoletters and there was no explicit information about the structure of the strings, readers must have relied on their ability to extract regularities directly from the visual input. This closely resembles the numerous visual statistical learning studies showing that observers compute co-occurrence probabilities for visual objects, and use these probabilities to create higher-level visual representations. For example, the experiments of Fiser and Aslin (2005), which we mentioned in the Introduction, demonstrated that observers utilize shape co-occurrence statistics to construct representations for complex shape sequences (e.g., shape quadruples).

By using a paradigm that bridges the visual word identification and the statistical learning literature (i.e., familiarization to visual statistics followed by lexical decision), we highlight the similarities between the processing of the ordered collection of visual objects that are typically investigated in the visual statistical learning experiments, and the ordered collection of pseudoletters that make up the strings investigated here. At a certain level of description, both types of stimuli are higher–level configurations of lower–level visual objects, in a hierarchy of complexity that builds on statistical regularities (e.g., co-occurrence statistics). Thus, our evidence is suggestive of the possibility that the ability to extract visual regularities may contribute to the processing of both non-linguistic and linguistic printed stimuli. In the visual word identification system, this statistical learning mechanism might serve the purpose of identifying cohesive chunks of letters that may become candidates for higher-order representations, which may then remain primarily orthographic (e.g., n-grams; Grainger & van Heuven, 2003; Whitney, 2001; morpho–orthographic chunks; Longtin et al., 2003; Rastle et al., 2004) or acquire a genuine morphological or lexical status if they become associated with specific meanings (e.g., lemmas; Crepaldi et al., 2010; Taft & Nguyen–Hoan, 2010).

A recent study by Chetail (2017) provided important early evidence for a link between statistical learning and visual word processing. Exposed to strings of pseudoletters similar to ours, Chetail's participants developed sensitivity to frequent bigrams and the single characters embedded in those bigrams. Our work complements these findings by extending the range of situations where statistical learning applies to the processing of strings: The clusters used in our study were longer than those used in Chetail (2017) (i.e., we used chunks that were 3- and 4-character long, whereas Chetail focused on bigrams), and featured a considerably more subtle statistical distribution (i.e., each chunk appeared in 10% of the lexicon in our work, compared to 50% in Chetail). Further, our chunks, much like real prefixes and suffixes, appeared in a fixed position within strings. These methodological differences bring us closer to recreating natural morphological processing. However, the core learning mechanism in both studies seems rather similar: Characters that frequently occur together get associated, thus potentially providing larger, higher-level functional units. In the experiments described here and in Chetail (2017), these units cannot be but purely visual/orthographic, which, as we have discussed above, may link to similar levels of representations in the visual word identification system (letter n-grams, morpho-orthographic chunks).

Further evidence supporting the proposition that visual word processing may be affected by a regularity learning mechanism comes from the Artificial Grammar Learning (AGL) literature (for reviews, see Christiansen, 2019; Frost et al., 2020; Perruchet & Pacton, 2006; Pothos, 2007; Reber, 1989). This body of research (historically operating largely in parallel to statistical learning research) demonstrated that observers learn the compositional regularities that characterize element sequences. For instance, in the seminal study of Reber (1967), participants who memorized strings generated from an artificial finite-state grammar were later able to distinguish between novel strings generated with the same grammar and random strings. This paradigm is of course similar to our paradigm where learners first observe familiarization strings and then judge whether or not previously unseen strings come from the same learning lexicon.

Interestingly, there is considerable agreement that the learning observed in AGL studies involves chunk learning to some extent (e.g., Christiansen, 2019; Perruchet & Pacton, 2006). Since the nature of grammatical systems is that they favour some element transitions more than others, grammatically-regular strings necessarily contain recurring chunks of elements (e.g., in a grammar where transitions *R-F* and *F-V* are highly likely, the chunk *RFV* is present in grammatical strings *SVDRFV*, *SVRFVDX*, *FVDRFVDX*; example from Perruchet & Pacton, 2006). Thus, an efficient way of distinguishing between grammatical and ungrammatical strings could be to rely on the frequent chunks present within a string. Regardless of whether such chunking occurs in parallel to, as a consequence of, or instead of rule learning, AGL research converges with our study in the sense that it clearly points to the importance of regularity learning for the processing of letter strings, and possibly also real words (for a discussion, see Christiansen & Chater, 2016; Isbilen, McCauley, Kidd, & Christiansen, 2017; Thiessen et al., 2013).

Although we did not set out to test any specific statistical learning account, our data can be nevertheless referred to some of the frameworks aiming to identify the mechanisms underlying regularity learning (for reviews, see Frank et al., 2010; Giroux & Rey, 2009; Thiessen & Erikson, 2013; Thiessen et al., 2013). For example, our finding that readers showed sensitivity to the presence of affixes could be interpreted through the lense of the PARSER model (Perruchet & Vinter, 1998; 2002; Perruchet & Pacton, 2006). According to this model, learning materials are initially processed as a collection of primitives, but through association these primitives gradually become integrated into representations of higher-level units. In this view, readers in our study would initially process an affix as a collection of individual pseudoletters, but later, with repeated exposure, they would integrate them into a coherent representation for that specific affix. Such representations could then be utilized to inform the string judgments in the testing phase. A similar interpretation would be suggested by the Bayesian Chunking Learner model (BCL; Orbán et al., 2008; Fiser, Orbán, Lengyel, & Aslin, 2009), according to which observers exploit the statistical contingencies between individual visual objects to form representations for reappearing object chunks. Under the assumption that the familiarization strings in our study were processed as visual materials, the BCL would also expect our readers to construct distinct representations for the affixes.

Note, however, that neither of these models would explicitly predict our readers' sensitivity to the chunk positional properties, particularly if the familiarization strings comprised chunks in the string-initial position. Specifically, we observed that the extent to which readers became sensitive to chunks' position differed depending on whether chunks were presented in the beginning or the end of familiarization strings (i.e., the associated effect was considerably stronger in the experiment where chunks appeared in the string-initial position, as compared to the experiment where they appeared in the string-final position). This was explained by the results in the affix detection task, which revealed a processing advantage for string-initial material, independently on where affixes appeared in the familiarization lexicon. Curiously, a similar finding has been observed in the processing of real words and, more generally, letter strings. Several studies showed that letters appearing in the string-initial position are processed more efficiently than those in other positions (e.g., Hammond & Green, 1982; Mason, 1982; Scaltitti & Balota, 2013; Tydgat & Grainger, 2009). It has been suggested that this initial-position advantage is, at least partly, due to a rapid deployment of spatial attention to the beginning of letter strings (Aschenbrenner et al., 2017; cf. Scaltritti, Dufau & Grainger, 2018), a mechanism which could help readers process the beginning of words, in turn easing lexical access and identification (e.g., Clark & O'Regan, 1999; Cutler, Hawkins & Gilligan, 1985; Stevens & Grainger, 2003). Interestingly, therefore, the totality of our data points to a possibility that the ability to extract and represent statistical information in written language might be modulated by other cognitive processes, including attentional biases (see also Aslin & Newport, 2012; Arciuli, 2017; Thiessen et al., 2013).

The use of statistical learning in morphological processing could also be limited by other factors. For one, real languages are characterized by far more variability than the artificial stimuli typically used in laboratory experiments, and it is possible that the learning would change under more naturalistic statistical parameters. In the study described here, readers saw 10 pseudo-affixes, each occurring in 20 different strings. What would happen if these numbers would mirror real morphology (e.g., English language distinguishes over 50 suffixes; Déjean, 1998)? Intuitively, using a greater number of pseudo-affix chunks could lead to worse learning, because the statistics would become considerably more subtle, potentially making it more difficult to associate characters into chunks. On the other hand, such difficulty could be mitigated by allowing more time for learning - after all, outside of psychological labs, readers spend a considerable time mastering a language. And of course, as we have already discussed, regularities are not confined to a single (e.g, orthographic) level, but can exist on multiple levels of linguistic information, and in the mappings between these levels (e.g., *er* might be a derivational suffix signifying agency as in *painter*, it may be a comparative form of adjectives as in *bigger*, or simply be an embedded letter cluster as in *corner*). It is currently unknown to what extent the processing of written words is affected by the learning of purely visual-orthographic regularities when the rich network of linguistic information is available to the reader (e.g., when orthographic regularities exist in parallel to phonological or semantic information). To investigate this, one could envisage a set of experiments where different levels of linguistic information are gradually introduced into a carefully-controlled set of artificial visual stimuli. Such a research program would help to more closely recreate natural language processing, and to probe the possible interactions between orthographic, semantic, and phonological regularities. There is certainly much material for future research here.

Finally, we turn to discussing the implications of our data for accounts of reading acquisition, particularly with regard to how learners become sensitive to the morphological structure of written words. The discovery of morphological regularities is considered an important step in the course of reading acquisition (Castles, Rastle & Nation, 2018). This is because it contributes to stronger links between orthography, phonology and meaning, and enables a more efficient recognition of words that is achieved through the process of chunking in which morphologically complex words are processed as familiar chunks (e.g., *interesting* can be read as two morphemes or chunks: *interest* and *ing*; Ehri, 2005; Nagy, Carlisle & Goodwin, 2014). It is believed that experiences with word and sentence processing help developing readers to learn the semantic, grammatical, and syntactic information that is conveyed by the morphology of the language to which they are exposed (e.g., Goodwin, Petscher, Carlisle & Mitchell, 2015; Nagy et al., 2014). However, while it is agreed that morphological learning occurs implicitly from the statistical properties of a given language (Goodwin et al., 2015), the precise mechanisms that underpin this knowledge acquisition are underspecified.

In our study, participants faced a task similar to that of developing readers - they were presented with an unfamiliar alphabet and lexicon, and their cognitive system was challenged to make sense of this new information. From this perspective, our evidence points to a possibility that morphological structure might be learnt also based on a bottom-up chunking mechanism, which can operate independently of explicit learning and other top-down processes (e.g., morpheme recognition driven by syntactic and semantic knowledge; Nagy et al., 2014). As we suggested above, such a bottom–up mechanism could serve the purpose of individuating statistically cohesive chunks as candidates for association with other linguistic levels (semantics, as in the case of morphemes, or phonology, as in the case of multi–letter graphemes, such as *sch* or *th*). In turn, acquiring such a morphological scaffolding for language could aid learners in constructing print-to-meaning mappings (see Yablonski, Rastle, Taylor & Ben Shachar, 2019).

Some evidence for a connection between statistical learning and learning to read comes from studies reporting a positive correlation between the two abilities among English (Arciuli & Simpson, 2012) and Norwegian developing readers (von Koss Torkildsen, Arciuli, & Wie, 2019). However, these data did not remain unchallenged. West et al. (2018) investigated the issue in a large cohort of English children, and reported a lack of correlation between performance in a Serial

Recall Task, which is often taken as a metric of implicit statistical learning, and word and nonword reading. Some inconsistency in this literature might be related to poor (inter-)reliability in some of the classic tests used to assess statistical learning, as reported in the same study by West et al. (2018) and in others (e.g., Schmalz, Moll, Mulatti, & Schulte-Körne, 2019; Siegelman, Bogaerts, & Frost, 2017). Clearly, in order to fully understand the role of statistical learning in reading acquisition a more systematic investigation is warranted. Given its importance in the process of reading development, future work should seek to provide direct links between the acquisition of morphological knowledge and statistical learning in children learning how to read. Further, it would be important to investigate whether artificial languages are approached by adults and developing readers in a similar manner. Whether the learning mechanisms of adult skilled readers are comparable to those of developing readers remains to be seen.

In sum, our evidence implies that the extraction of statistical regularities may play an important role in the processing of written language, particularly in the morphological domain. Previous studies on the visual identification of complex words have suggested that this process may be based, at least in part, on general visual mechanisms building on letter co-occurrence probability. The use of an artificial script in the present study enabled us to obtain important preliminary evidence suggesting that several phenomena previously limited to the visual processing of real linguistic materials can in fact occur without the contribution of semantic, phonological or syntactic information. This highlights a possible continuity between visual word identification and non–linguistic visual learning, both ontogenetically (Dehaene & Cohen, 2007) and phylogenetically (Grainger, Dufau, Montant, Ziegler & Fagot, 2012).

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